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*Optimal Allocation of Land for Training and Non-training Uses (OPAL)*

## **OPAL Netlogo Land Condition Model**

Application and Validation at Fort Riley, KS

Daniel Koch, James Westervelt, Andrew Fulton, Natalie Myers,  
Scott Tweddale, Dick Gebhart, Ryan Busby, Anne Dain-Owens,  
and Heidi Howard

August 2014



OPAL team measuring above and below-ground biomass after treatments at Fort Riley, KS.

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## Abstract

Proper management of military training lands is critical to ensure availability of training lands, and thereby ensure mission readiness. However, installation land management practices often support a broader mission than simply maintaining the land in a condition suitable for training; they also help installations to meet environmental requirements. The Optimal Allocation of Land for Training and Non-Training Uses (OPAL) Program was developed to provide a systematic approach to enable military land managers and trainers to estimate biomass responses to training/management scenarios (training, mowing, and burning). This report documents a field validation of the OPAL model at Fort Riley, KS, and makes recommendations for system improvement.

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## Preface

This study was conducted for the Assistant Secretary of the Army for Acquisition, Logistics, and Technology (ASAALT), under A896 Project (AMSCO 622720089600), “Optimal Allocation of Land for Training and Non-Training Uses.” The technical reviewer was Alan B. Anderson, CEERD-CV-T.

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# 1 Introduction

## 1.1 Background

Proper management of military training lands is critical to ensure availability of training lands, and thereby ensure mission readiness. Sustainable training land management complements the military mission by minimizing detrimental environmental impacts of maneuver training. Army Regulation (AR) 350-19 assigns responsibilities and prescribes policies for maximizing the capability, availability, and accessibility of ranges through the Sustainable Range Program (SRP). A core component of the SRP is the Integrated Training Area Management (ITAM) Program, which provides the Army the capability to manage and maintain training lands by integrating mission requirements with environmental requirements and appropriate land management practices (HQDA 2005). To date, many studies have estimated the impacts of military training activities on installation lands (Ricci et al. 2012).

However, installation land management practices often support a broader mission than simply maintaining the land in a condition suitable for training. The Army's "ecosystem approach" to land management supports multiple-use activities, when those activities are compatible with mission requirements, including agriculture and grazing outleases (USAEC 2011). As a Federal agency, the Army is also required by the US Endangered Species Act (ESA) to conserve Federally listed Threatened and Endangered Species (TES) on installation lands. The Army often makes proactive management efforts to eliminate potential conflicts between Threatened, Endangered, Proposed, and Candidate (TEPC) species and military mission and management efforts (USAEC 2009). Installations' Integrated Natural Resources Management Plans (INRMPs) include practices that benefit the conservation of species of concern, e.g., by incorporating plans to enhance or preserve critical habitat through such management practices as controlled burns.

Generally, military training land management and maintenance practices support two primary objectives: (1) to maintain lands for military training and (2) to meet environmental requirements. Proactive land management practices that support potentially conflicting land uses must take a systematic approach that considers, coordinates, and integrates complex land

impacts. Development of the Optimal Allocation of Land for Training and Non-Training Uses (OPAL) Program was undertaken to provide such a systematic approach in the form of modeling software that can provide military land managers and trainers with the capability to estimate biomass responses to historical or planned training/management scenarios, and that can also function as a research tool that will improve the understanding of the influences on military land use (training and non-training) on the dynamic and complex nature of above- and below-ground biomass. This report documents a field application of the Optimal Programming of Army Lands (OPAL) model at Fort Riley, KS.

## **1.2 Objectives**

The overall technical objective of the OPAL project is to develop approaches to estimate cumulative land disturbance on military training lands through above- and below-ground biomass responses by merging current biomass disturbance methods/models with OPAL field data to capture disturbance regimes for military land managers.

The specific objective of this phase of work was to perform and document a field application of the OPAL model at Fort Riley, KS. This initial application was undertaken to:

1. Validate the OPAL model under “real world” conditions
2. Outline required steps to transfer the model to other installations
3. Promote a common view among military land management and the training community at multiple levels (e.g., installation and headquarters) of training land utilization and interconnectivity of individual land uses and their impacts on training land quality.

## **1.3 Approach**

The objectives of this project phase were met through the following steps:

1. A 4-year research study under the OPAL project collected field measurements of above- and below-ground biomass in response to training, controlled burn, and haying treatments. Additionally, above-ground biomass data provided by the Fort Riley ITAM program were obtained for calibration and validation purposes.
2. These data were used to create a land condition model based on existing vegetation growth and soil moisture models.

3. The overall modeling approach estimated above- and below-ground biomass growth and death given weather conditions and typical land uses for a grassland military installation (training, controlled burn, and mowing/haying).
4. OPAL simultaneously modeled above- and below-ground biomass for an undisturbed condition (no land use impacts) for comparison and then used above- and below-ground biomass as an indicator of training land condition for use in training land management and planning.

## **1.4 Scope**

The scope of this report is to provide a description of the land condition model its application at Fort Riley. The report provides a description of the site-specific data required to operate the model as well as the calibration efforts required. Finally, the report documents the validation effort based on field and remote sensing data.

## **1.5 Mode of technology transfer**

This report will be made accessible through the World Wide Web (WWW) at URLs:

<http://www.cecer.army.mil>

<http://libweb.erdg.usace.army.mil>

## 2 Materials and Methods

### 2.1 Model description

#### 2.1.1 Fundamental equations

##### 2.1.1.1 Above-ground biomass

This section provides an overview of the main functions of the OPAL vegetation growth model and their parameters. Myers et al. (2013) describes the model and documents the associated NetLogo code more fully. The OPAL vegetation growth model is based on components of the CENTURY model (NREL 2006, Parton et al. 1993.). CENTURY is a computer model of plant-soil ecosystems that simulates the dynamics of grasslands, forest, crops, and savannas with a focus on nutrient (carbon, nitrogen, phosphorous, and sulfur) cycle estimation. The plant production submodel of the CENTURY model was used as the basis for the OPAL biomass modeling approach. The CENTURY model calculates potential plant production as a function of soil temperature, soil moisture, and a self shading factor:

$$P_p = P_{max} * T_p * M_p * S_p \quad (1)$$

where:

$P_p$  = above-ground potential plant production rate ( $\text{g m}^{-2} \text{ month}^{-1}$ )

$P_{max}$  = maximum potential above-ground plant production rate

$T_p$  = effect of soil temperature on growth (unitless)

$M_p$  = effect of soil moisture on growth (unitless)

$S_p$  = effect of plant shading on growth (unitless)

$T_p$  and  $M_p$  are calculated by equations 2 and 3, respectively.

$$T_p = \exp \left[ \left( \frac{ppdf(3)}{ppdf(4)} \right) * \left( 1 - \left( \frac{ppdf(2)-c_{temp}}{ppdf(2)-ppdf(1)} \right)^{ppdf(4)} \right) \right] * \left( \frac{ppdf(2)-c_{temp}}{ppdf(2)-ppdf(1)} \right)^{ppdf(3)} \quad (2)$$

where:

$T_p$  = effect of soil temperature on growth (unitless) (tempM in NetLogo Model)

ppdf(1) = optimum temperature for production for parameterization of a Poisson Density Function curve to simulate temperature effect on growth. (30 for Konza - crop.100)

- ppdf(2) = maximum temperature for production for parameterization of a Poisson Density Function curve to simulate temperature effect on growth. (45 for Konza-crop.100)
- ppdf(3) = left curve shape for parameterization of a Poisson Density Function curve to simulate temperature effect on growth. (1 for Konza-crop.100)
- ppdf(4) = right curve shape for parameterization of a Poisson Density Function curve to simulate temperature effect on growth. (2.5 for Konza-crop.100)
- ctemp = average soil surface temperature (°C).

$$M_p = 1.0 + \left( \frac{\left( \frac{avh2o(1) + prcurr(month) + irract}{pet} \right) - pprpts(3)}{pprpts(3) - pprpts(1) - pprpts(2) * wc} \right) \quad (3)$$

where:

- $M_p$  = effect of soil moisture on growth (unitless) – (limited from 0.0-1.0)
- avh2o(1) = water available to plants for growth in soil profile (cm)
- prcurr(month) = precipitation in current month (cm)
- irract = amount of irrigation water in the current month (cm) – will not need for Riley
- pet = potential evapotranspiration (PET) rate for month (cm) (see below)
- pprpts(1) = the minimum ratio of available water to PET, which would completely limit production assuming water content is equal to 0; Valid Range: 0.0 to 1.0. (For Konza = 0, fix.100)
- pprpts(2) = the effect of water content on the intercept, which allows the user to increase the value of the intercept and thereby increase the slope of the line (For Konza = 1.0, fix.100)
- pprpts(3) = the lowest ratio of available water to PET at which there is no restriction on production; Valid Range: 0.0 to 1.0 (For Konza = 0.8, fix.100)
- wc = afield(1) – awilt(1) = field capacity of top soil layer – wilting point of top soil layer (unitless fraction 0.0-1.0).

#### 2.1.1.2 Below-ground biomass

The CENTURY model estimates below-ground biomass according to a root-to-shoot ratio estimated from the cumulative rainfall to that point (NREL 2006) (Equation 4). However, the above-ground biomass model described in the previous sub-section estimates live above-ground bio-

mass. While above-ground biomass may die during senescent periods, below-ground biomass of most grassland species remains dormant during this period. To model this behavior, the OPAL NetLogo model assumes below-ground biomass temporarily remains unchanged if estimated below-ground biomass (from the root-to-shoot ratio) is lower than the previous time step below-ground biomass. Following the estimation of a below-ground biomass due to root-to-shoot ratio, root death is calculated based on available soil moisture. As modeled, above-ground biomass growth essentially drives below-ground biomass growth while soil moisture conditions drive below-ground biomass death:

$$RS_{Ratio} = \frac{(100 + \text{cumulative precipitation} * 7)}{-40 + \text{cumulative precipitation} * 7.7} \quad (4)$$

### 2.1.1.3 Soil temperature and moisture

Soil temperature is calculated from the maximum and minimum air temperatures for the week and above-ground biomass cover (NREL 2006). Calculated soil temperature is an average of the maximum and minimum calculated from the air temperatures. The soil temperature is calculated in degrees Celsius (°C) and is assumed to be uniform across the root depth.

$$t_{soilmin} = t_{airmin} + 0.004 * \text{abovegroundbiomass} - 1.78 \quad (5)$$

$$t_{soilmax} = t_{airmax} + \left( \frac{25.4}{1 + 18 * e^{(-0.2 * t_{airmax})}} \right) * (e^{-0.0035 * \text{abovegroundbiomass}} - 0.13) \quad (6)$$

$$t_{soil} = \frac{t_{soilmin} + t_{soilmax}}{2} \quad \text{Eq. 7}$$

Soil moisture is then calculated by the following moisture balance model:

$$\theta_t = \theta_{t-1} + \frac{\left[ i * \frac{1}{10} \left[ \frac{cm}{mm} \right] - ET_{obs} - K_{sat} * K_r * 7 \left[ \frac{day}{week} \right] * 24 \left[ \frac{hr}{day} \right] \right]}{L} \quad (7)$$

where:

$\theta_t$  = soil moisture (m/m)

$\theta_{t-1}$  = soil moisture from previous week (m/m)

$ET_{obs}$  = observed or actual evapotranspiration (cm/week)

$K_{sat}$  = saturated hydraulic conductivity (cm/hr)

$K_r$  = relative hydraulic conductivity (unitless) calculated using Van Genuchten's closed-form equation for estimating unsaturated hydraulic conductivity (Van Genuchten 1980).

$L$  = depth of soil layer.

Potential evapotranspiration is estimated using the Blaney-Criddle Method (Brouwer and Heibloem 1986, Schwab et al. 1993). The Blaney-Criddle Method is a simple, empirical evapotranspiration model and is a function of average temperature and mean daily percentage of annual daytime hours.

$$ET_o = p * (0.46 * t_{mean} + 8) \quad (8)$$

where:

$ET_o$  = potential evapotranspiration rate (mm/day)  
 $p$  = mean daily percentage of annual daytime hours  
 $t_{mean}$  = mean weekly temperature (°C).

As described by Dyck (1983), potential evapotranspiration does not accurately describe the actual evapotranspiration observed. If soil moisture is lower, associated actual evapotranspiration rates for soil water balance calculations will be lower. A simple method for estimating actual evapotranspiration using relative soil moisture does not require any additional parameters and models the reduction of actual evaporation with the reduction of available soil moisture:

$$ET_{obs} = ET_{pot} * (\theta_i - \theta_{wp}) / (\theta_{sat} - \theta_{wp}) \quad (9)$$

where:

$ET_{obs}$  = observed or actual evapotranspiration  
 $ET_{pot}$  = potential evapotranspiration  
 $\theta_i$  = soil moisture (m/m)  
 $\theta_{wp}$  = soil moisture at wilting point (m/m)  
 $\theta_{sat}$  = soil moisture at saturation (m/m)

#### 2.1.1.4 Training distribution and impacts.

Historically, military land management has had a critical (and unmet) need to estimate training distribution and impacts. Generally, the installations' Range Facility Management Support System (RFMSS) databases are used to attempt to quantify training impacts (Davis 2005). While implemented by Army installations, RFMSS is lacking in several aspects:

1. There is a paucity of detailed training intensity information.
2. The spatial scale, which is usually at a training area level, leads to an over-estimation of the spatial distribution of training impacts.
3. Data are often not recorded as thoroughly as necessary.

The US Army Training and Testing Area Carrying Capacity (ATTACC) was developed and implemented as part of the ITAM program (USAEC 1999). The overall objective of the ATTACC methods is to estimate training land carrying capacity by estimating training impacts. The ATTACC methodology, which links training impacts to the RFMSS database to estimate overall training impact, may be used to estimate the number of “maneuver impact miles” (MIMs), the equivalent damage of one M1A2 traveling 1 mile, trained in that training area by:

$$MIM = \sum_{v=1}^v (Number_v * Mileage_v * VSF_v * VOF_v * VCF_v * LCF) \quad (10)$$

where:

- MIM = maneuver impact mile
- V = vehicle type (Dimensionless)
- v = number of types of vehicles training in area for the week
- Number<sub>v</sub> = number vehicles of type, V, training in area
- Mileage<sub>v</sub> = average mileage driven per vehicle, V
- VSF<sub>v</sub> = vehicle severity factor
- VCF<sub>v</sub> = vehicle conversion factor
- VOF<sub>v</sub> = Vehicle off-road factor
- LCF = Land condition factor (Sullivan and Anderson 2000).

Two levels of training data fidelity can be used as inputs to the model: (1) RFMSS level data including all of the information described in Equation 11 except for the vehicle mileage, or (2) a generic indication of training intensity, quantified as the “average number of MIMs per training area,” which ranges from 1 to 3.

Using methodologies described by Svendsen et al. (2012), the change in vegetation to each patch given the training load was estimated as:

$$\Delta(AGB) = \frac{MIM[mi] * MCF \left[ \frac{m^2}{mi} \right] * AGB \left[ \frac{g}{m^2} \right]}{A[m^2]} \quad (11)$$

where:

- AGB = above-ground biomass [g/m<sup>2</sup>]
- MIM = maneuver impact miles [mi]
- MCF = MIM conversion factor = area impacted by one MIM [m<sup>2</sup>/mi]
- A = total area of patch [m<sup>2</sup>].



Estimates of training impact on below-ground biomass were made based on literature review and field data. The LCF, which accounts for different in training impact due to moisture condition, is calculated by taking a ratio of a reference soil moisture rating cone index (RCI) to the actual soil moisture RCI to the 5/3rds power (Sullivan and Anderson 2000).

As documented in ATTACC methodologies, the distribution of training across maneuver areas is difficult to estimate. Ayers et al. (2000) and Koch et al. (2012) have discussed methods to obtain high spatial and temporal resolution training distribution and impact data through global positioning system (GPS) based vehicle tracking systems; however this is likely not economically or practically feasible for a large number of training events across many installations. As such, methods to estimate a distribution of training within a training area (e.g., lowest resolution data widely available through RFMSS) are desired.

An approach developed by Guertin (2000) for Fort Hood estimated a probability surface that defines areas more likely to be impacted by training maneuvers. This approach is based on a logistic regression of observed disturbance data on a set of independent variables that appeared to influence training distribution (slope, vegetation type, installation region, and distance from maintained roads). Fang et al. (2002) performed an uncertainty analysis of the disturbance model developed by Guertin and concluded that the error and uncertainty in the vegetation map were the dominant sources of mapping uncertainty. This approach provides a better solution than assuming an even distribution across each training area.

#### *2.1.1.5 Burning and haying/mowing land management impacts*

A burning component to the above-ground biomass was added based on CENTURY model assumptions (NREL 2006). The CENTURY model assumes three levels of fire intensity that remove between 60 and 80% of the above-ground biomass. For the initial OPAL model development and demonstration, a medium fire intensity (70% reduction) was assumed since fire intensity was not an attribute of the documented proscribed burn/wildfire dataset. As such, if the burning data state that a particular patch was burned during the week, the above-ground biomass component was reduced by 70% from the non-burned calculated value. Below-ground biomass was determined based on a mixed linear model where given soil conditions, percent increases, or decreases in below-ground biomass are estimated by treatment conditions (Fulton 2013).

A haying component (similar to the previously described burning component) was also added. The model assumes that 90% of the above-ground biomass is removed if the haying schedule predicts that the referenced patch was hayed during that time schedule. The impact on below-ground biomass was obtained from field data and a literature review.

### 2.1.2 Use of OPAL NetLogo model

NetLogo is a multi-agent programmable modeling environment with a simple user interface. Its large dictionary of functions and extensions, including a Geographic Information System (GIS) extension, make NetLogo a powerful platform for natural resources modeling applications. The OPAL vegetation condition model uses a simple user interface that contains the scenario selector tools, a graphic display of the area modeling, and data output plots (Figure 1). Sections 2.2 and 2.3 of this document outline the site-specific data and parameters for a given location.

Once the model is set up for a given area, users can model and test various alternative management or training schedules with different weather inputs to compare the resulting impacts to training land resources (Figure 2). The OPAL Vegetation Condition Model User Manual (Westervelt et al. 2013) describes OPAL model use more completely.

Figure 1. OPAL vegetation condition model user interface.

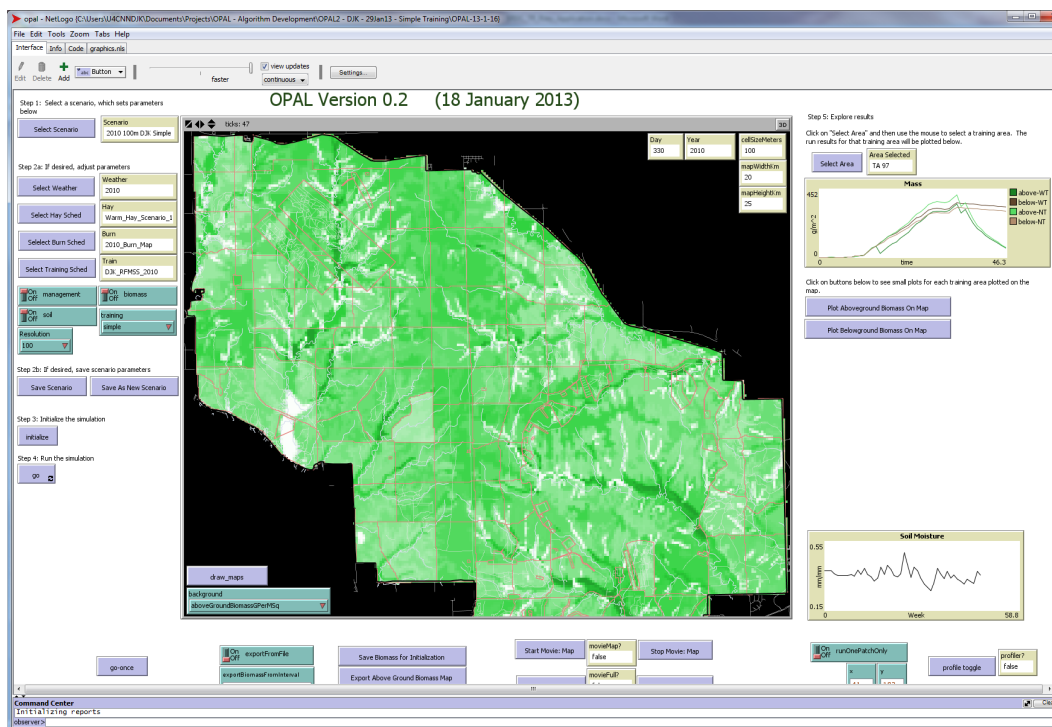
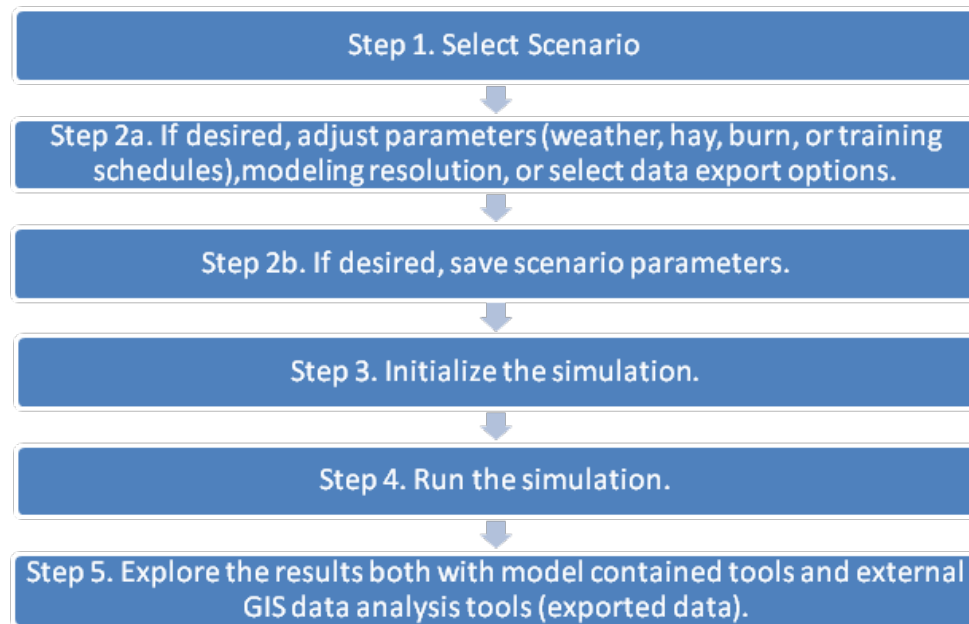


Figure 2. Schematic of OPAL vegetation condition model user process.



## 2.2 Site description

### 2.2.1 Fort Riley, KS site description

Fort Riley is situated in the Bluestem Prairie region of northeastern Kansas, within a 1.6 million ha region in eastern Kansas containing the largest un-tilled tallgrass prairie landscape in the world (Knapp and Seastedt 1998). The installation encompasses a land area of 41,154 ha, which contains a mix of native prairie and introduced vegetation. Tall grasses dominate this area, and wood and shrub lands occur mainly in the stream valleys (Althoff and Thien 2005). Fort Riley is located approximately 25 km northwest of the Konza Prairie Biological Station, a long-term tallgrass prairie ecological research center. The proximity to the Konza Prairie makes Fort Riley an ideal location for model development as the CENTURY model was parameterized for the Konza Prairie (Parton et al. 1993).

Grasslands (ca. 32,200 ha), shrublands (ca. 1600 ha), and woodlands (ca. 6000 ha) form the three major vegetation communities on Fort Riley. Big bluestem (*Andropogon gerardii*), Indiangrass (*Sorghastrum nutans*), switchgrass (*Panicum virgatum*), and little bluestem (*Schizachyrium scoparium*) dominate the grasslands with other grasses and forbs occurring in lesser abundance. Buckbrush (*Symphoricarpos orbiculatas*), smooth sumac (*Rhus glabra*), and rough-leaved dogwood (*Cornus drummondii*) dominate the shrublands vegetation community. These

shrublands communities generally occur along woodland edges and in isolated patches in grassland areas while woodlands typically occur along riparian lowlands. The woodlands are characterized by chinquapin oak (*Quercus muhlenbergii*), bur oak (*Quercus macrocarpa*), American elm (*Ulmus americana*), hackberry (*Celtis occidentalis*), and black walnut (*Juglans nigra*) (Koch et al. 2012).

Since the early 1940s, Fort Riley has been home to a variety of military training activities including field maneuver training mechanized/armored vehicles, combat vehicle operations, mortar and artillery fire, and small-arms fire. Currently, Fort Riley is home to three brigade combat teams, a Combat Aviation brigade, a Sustainment Brigade, and Division Headquarters for the 1<sup>st</sup> Infantry Division (HQDA 2010). The majority of mechanized maneuver activities has occurred on the northern 75% portion of Fort Riley (17 of the 18 designated training areas ranging from 577–3,024 ha) for the past 4 decades. The most heavily used maneuver areas are occupied up to 210 days out of the year. Typical maneuvers by large tracked and wheeled vehicles that traverse thousands of hectares in a single training exercise can cause impacts ranging from minor soil compaction and lodging of standing vegetation to severe compaction and complete loss of vegetative cover in areas with concentrated training use.

Fort Riley uses prescribed burning as a mechanism to sustain training mission by enhancing native prairie (HQDA 2010). The objectives of prescribed burning are to maintain open space for training, reduce wildfire risk, reduce woody plant encroachment, maintain wildlife cover, and control sericea lespedeza. Most often, prescribed burns are conducted from 1 September to 30 April annually. Despite precautions to minimize fire risk, wildfires resulting from training activities may occur during any season on the installation.

Fort Riley leases over 19,000 ha of warm and cool season grasslands for hay harvesting as 5-year agricultural outleases (HQDA 2010). The objectives of hay outleases are to maintain the open space for military training, reduce the risk of wildfires by reducing the accumulation of standing dead vegetation, reduce woody plant encroachment, enhance wildlife cover, control sericea lespedeza, and reduce the expense for ground maintenance mowing. Warm season grasses are cut during the period of 15 July to 15 August each year while cool season grasses are cut during the period 1 May to 30 September (Dix 2010).

## 2.2.2 Fort Riley, KS input data

### 2.2.2.1 Maps and spatial data

The NetLogo modeling environment has a GIS extension to provide the ability to load vector and raster GIS data into a model. Site geospatial data is loaded into the OPAL NetLogo vegetation condition model to establish model boundaries and apply attributes to the areas being modeled. The geospatial data used in the model include the site boundary, training areas, and soils map. For display purposes, road and stream maps were used. The training area vector file contains training area names as an attribute. Due to the nature of the model, the soils vector file requires a number of attributes, including:

- soil depth
- soil permeability
- soil water holding capacity
- soil texture
- wilting point
- saturation point
- bulk density
- average biomass production
- soil texture abbreviation.\*

This data can be obtained from county soil surveys based on the soil texture or can be downloaded from SSURGO.

### 2.2.2.2 Weather

Weekly weather data are used to calculate total precipitation, maximum, minimum, and average temperature for each weekly time step. Weather data for Fort Riley were obtained using the Applied Climate Information System (ACIS) Web Services distributed data system. This system weather data may be obtained through an http request from a web browser with a properly formatted URL (ACIS 2012). For Fort Riley, data from US Historical Climatology Network (USHCN) ID 144972 located in Manhattan, KS were used. For example, a comma separated variable text file for the daily

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\* According to the US Department of Agriculture-Natural Resources Conservation Service (USDA-NRCS) Soil Survey Geographical Database (SSURGO) Standard (e.g., Silty Clay Loam is SICL, Sandy Clay Loam is SCL, etc), and Unified Soil Classification System (USCS) group symbol (e.g., CH, SP-SM, etc.)

maximum temperature, minimum temperature, average temperature, and precipitation at Manhattan, KS for 2009 is available for download from:

<http://data.rcc-acis.org/StnData?sld=144972&sDate=2009-01-01&eDate=2009-12-31&elems=maxt,mint,avgt,pcpn&output=csv>

### 2.2.2.3 Schedules

#### 2.2.2.3.1 Training

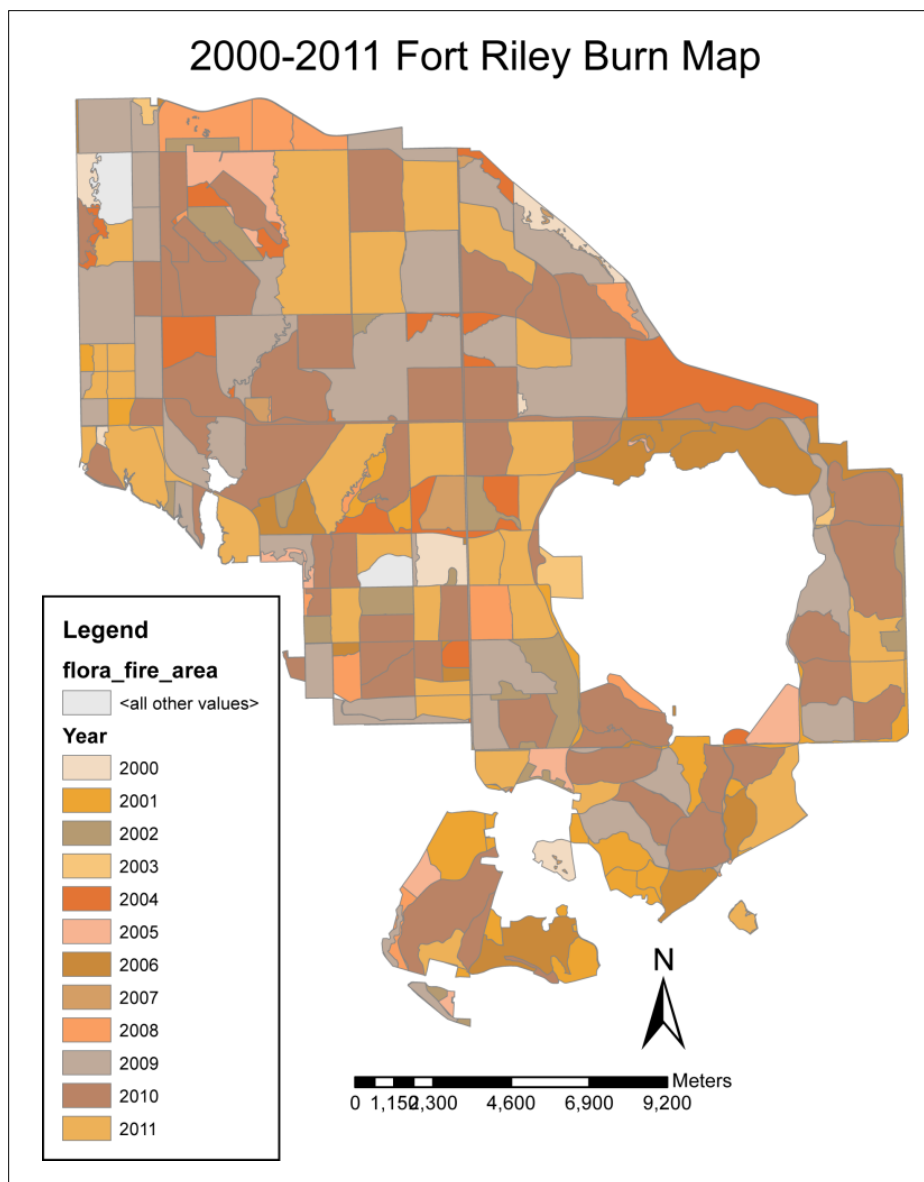
Training data from 2000–2011 were obtained from the RFMSS database for Fort Riley. This data contained the date and location each training area was used, the number and type of vehicles using the area, and the Vehicle Severity Factor (VSF) and Vehicle Conversion Factor (VCF) for each vehicle used. This level of data allows for an estimation of MIMs using the ATTACC methodology described above with an assumption of distance traveled. However, the quality and accuracy of this data depends on the level of detail input at the installation level. The data quality and accuracy varies by installation and by year.

In addition to past impacts, this model was created to assess future impacts given different land management scenarios. As such, a simple estimation of training intensity was desired. The OPAL NetLogo schedule creator software allowed the creation of simplistic training schedules on a weekly interval. The schedule applies a generic training intensity, rated from Level 0 to Level 3. Depending on the application, these generic intensities can be associated with an average level of MIMs. Schedules were created using this method based on the RFMSS data from 2000–2011.

#### 2.2.2.3.2 Burning

Fort Riley maintains a geospatial dataset that delineates controlled burn and wildfire burn events (Figure 3). Fort Riley specifies each burn polygon according to the burn date, burn priority, and area burned. The dataset also defines whether the burn was a controlled burn or wildfire. This dataset was used to create yearly burn schedules at a weekly time step using the OPAL NetLogo schedule creating program.

Figure 3. Fort Riley 2000–2011 Burn Map. Note: Most polygons are burned more than once in the 12-year period. The map depicts the most recent burn year for each polygon.

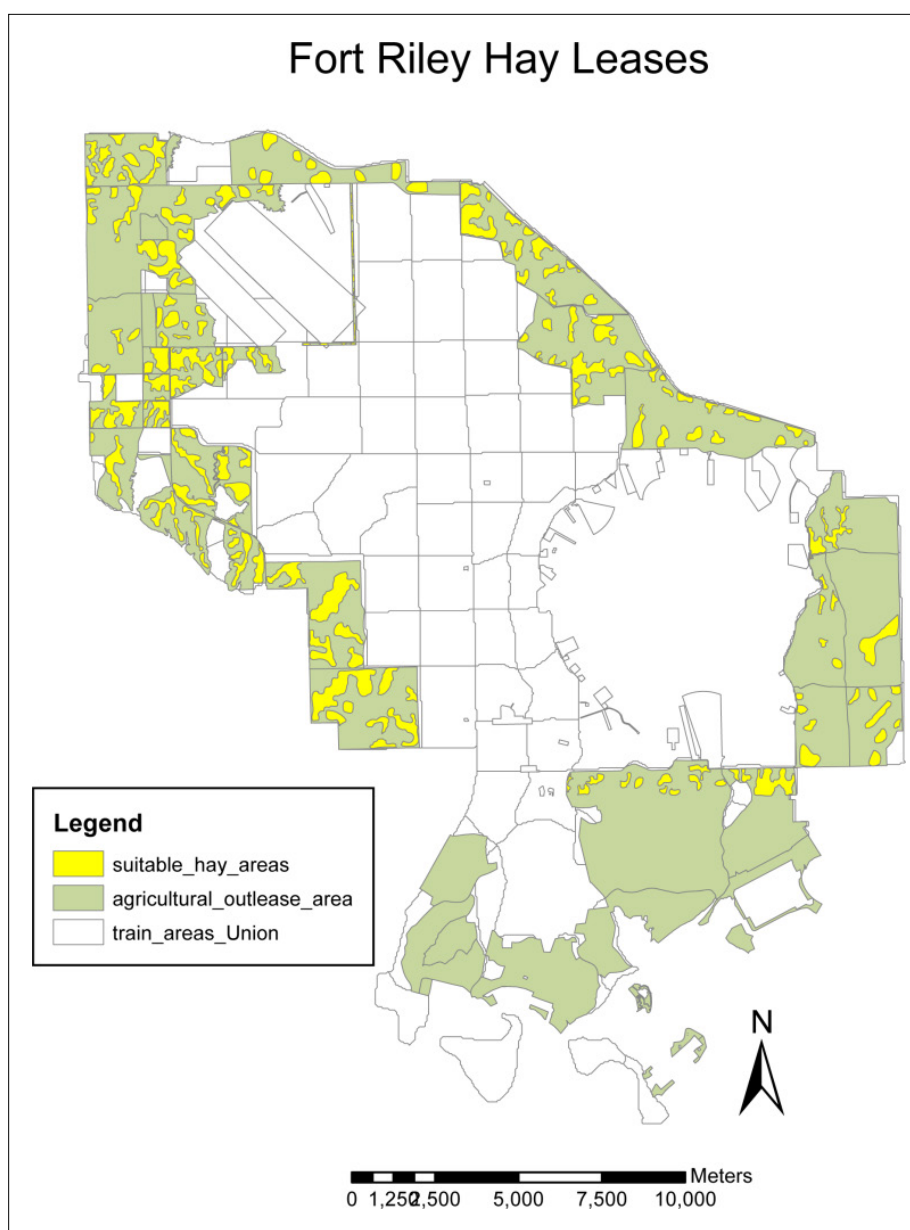


### 2.2.2.3.3 Haying

Under Fort Riley's agricultural outlease program, 21 areas ranging in area from approximately 130 –1900 ha are leased in 5-year terms (Figure 4). These leases are specified by cool or warm season grasses. Warm season grasses are cut during the period of 15 July to 15 August each year while cool season grasses are cut during the period 1 May to 30 September. However, actual harvest dates are not available as the level of detail contained in the haying geospatial databases is lower than that obtained for the burning map.

An interview with the Fort Riley outreach manager revealed that, with certain exceptions, approximately 10 to 20% of each lease is hayable (Spohn 2012). These limitations are due to slope, vegetation type, streams, and conservation practices such as buffer strips, grassed water ways, and field plots. The most suitable haying areas in each lease area were identified based on the percentage hayable, slope, and land cover class (grassland versus wooded, streams, etc.) (Figure 4). From these estimations, the lease areas and their requirements, the OPAL NetLogo schedule creating program was used to create a yearly hay schedule in weekly time steps.

Figure 4. Fort Riley agricultural outreach areas with suitable haying areas delineated.





#### 2.2.2.4 Site-specific parameters

While developing the OPAL NetLogo vegetation condition model, every effort was taken to minimize the number of site-specific parameters required to input into the model. For example, soil specific variables were chosen that could be easily obtained from the SSURGO database for a vast majority of the continental United States. However, some of the vegetation growth parameters and other model parameters could not be obtained from widely available datasets. Additionally, the use of the CENTURY biomass growth model required the use of certain site or crop specific parameter estimations (Parton et al. 1993). Table 1 lists the required site-specific parameters, the parameter definition, Fort Riley parameter estimate, and the source for each parameter estimate. Most of these parameters can be estimated from CENTURY documentation, soils data, or the PET process described in Appendix A.

**Table 1. OPAL NetLogo vegetation condition model site-specific parameters.**

Site-Specific Parameter	Parameter Definition	Fort Riley Parameter Estimate	Parameter Estimation Source
ppdf_1	Optimal temperature for vegetation production for parameterization of temperature effect on growth curve.	30	NREL (2006); crop.100 parameter file
ppdf_2	Maximum temperature for vegetation production for parameterization of temperature effect on growth curve.	45	NREL (2006); crop.100 parameter file
ppdf_3	Left curve shape for parameterization of a Poisson Density Function curve to simulate temperature effect on growth.	1	NREL (2006); crop.100 parameter file
ppdf_4	Right curve shape for parameterization of a Poisson Density Function curve to simulate temperature effect on growth.	2.5	NREL (2006); crop.100 parameter file
pprpts_1	The minimum ratio of available water to monthly PET, which would completely limit production.	0	NREL (2006); fix.100 parameter file
pprpts_2	The effect of water content on the intercept, allows the user to increase the value of the intercept and thereby increase the slope of the line.	1.0	NREL (2006); fix.100 parameter file
pprpts_3	The lowest ratio of available water to PET at which there is no restriction on production.	0.8	NREL (2006); fix.100 parameter file
pmax	Maximum potential plant production rate per week ( $\text{g m}^{-2} \text{ month}^{-1}$ ).	58.0	NREL (2006); crop.100 parameter file
AveProdGmSq	Average maximum biomass production for year from SSURGO or soil survey for Fort Riley area.	622.4	SSURGO database (NRCS)

Site-Specific Parameter	Parameter Definition	Fort Riley Parameter Estimate	Parameter Estimation Source
	Modifies pmax by soil type according to the soil capacity to support vegetation growth ( $\text{g m}^{-2} \text{ year}^{-1}$ ).		
PETfunc_1	3 <sup>rd</sup> degree polynomial coefficient for equation estimating mean daily percentage of daytime hours for given latitude (See Appendix A for calculation).	0.000001	Brouwer, C. and M. Heibloem (1986)
PETfunc_2	2 <sup>nd</sup> degree polynomial coefficient for equation estimating mean daily percentage of daytime hours for given latitude (See Appendix A for calculation).	0.0003	Brouwer, C. and M. Heibloem (1986)
PETfunc_3	1 <sup>st</sup> degree polynomial coefficient for equation estimating mean daily percentage of daytime hours for given latitude (See Appendix A for calculation).	0.013	Brouwer, C. and M. Heibloem (1986)
PETfunc_4	Constant term for polynomial equation estimating mean daily percentage of daytime hours for given latitude (See Appendix A for calculation).	0.18	Brouwer, C. and M. Heibloem (1986)

## 2.3 Model calibration

### 2.3.1 Land management and training impacts on below-ground biomass

For this modeling effort, estimates of below-ground biomass dynamics in response to disturbances such as surface perturbation (military training), burning, and haying/mowing in tallgrass prairie ecosystems was required. The treatments of interest included three levels of disturbance/impact (control, light, heavy) in a factorial arrangement with three types of management practices (control, burning, haying). Because the initial modeling efforts were focused on Fort Riley, KS, obtaining root biomass data from Tallgrass, Flinthills, or Konza Prairies was the primary driver as these ecosystems are most similar to those at Fort Riley. Therefore, a comprehensive literature review was conducted whereby data from as many different sources, seasons, and years as possible were collected.

Collection of root biomass data is very difficult and time consuming and often requires specialized sampling equipment and supplies, which results in significant additional expense to the experimental study. As such, scientific literature reporting root biomass data is relatively rare compared to that reporting above-ground biomass. Therefore, this effort focused the

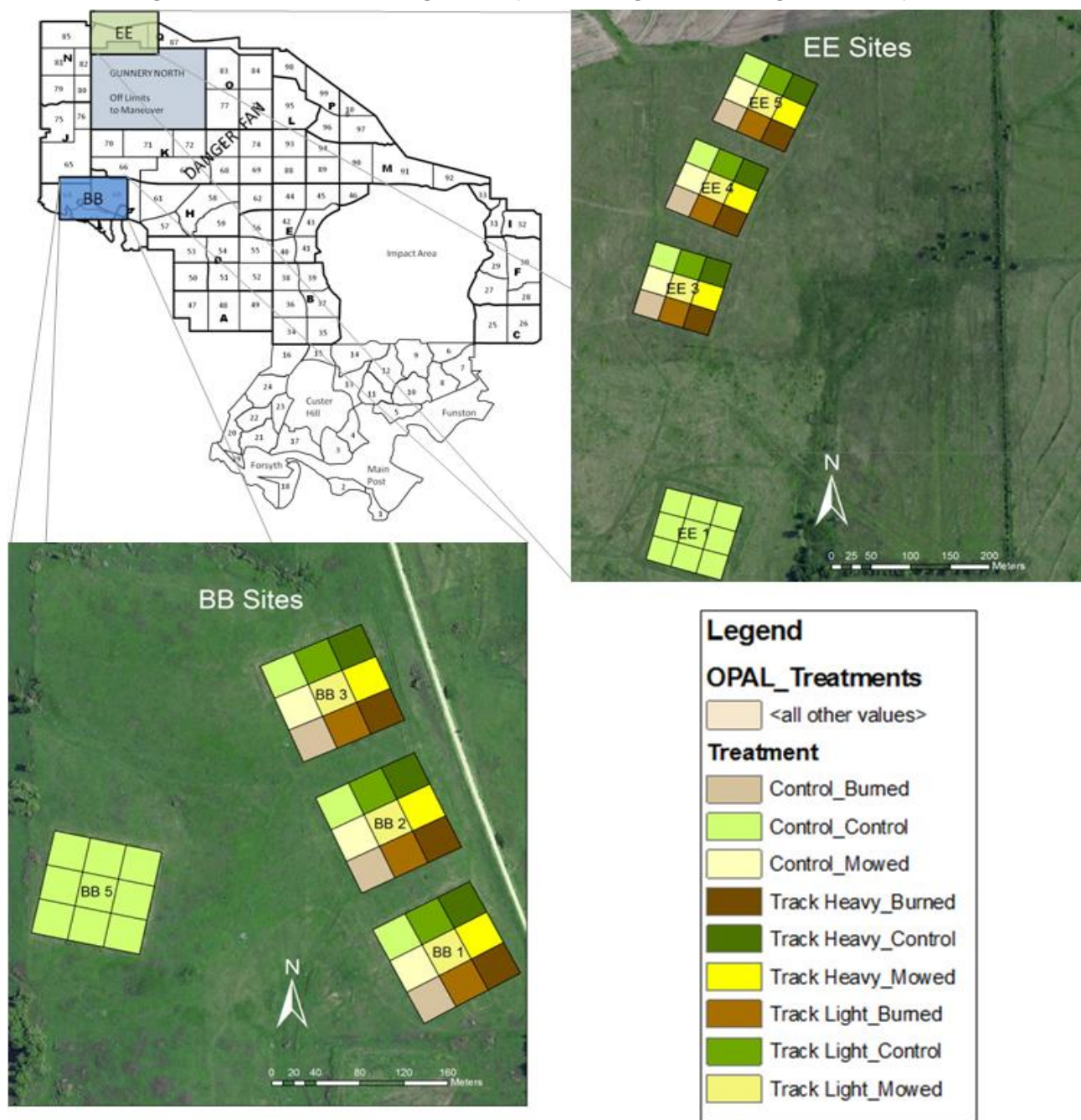
literature searching efforts on locating any data that might pertain to root biomass in Tallgrass Prairies.

Some of the root biomass data came from studies that used field plots where disturbance treatments were imposed and plant roots subsequently harvested using soil cores, soil monoliths, soil blocks, or soil trenches. Other root biomass data were inferred using field studies that measured changes in microbial biomass due to burning or haying/mowing. Since microbial biomass is considered a sensitive indicator of changes in quality and quantity of organic matter inputs from root systems, any change in microbial biomass can be used as a surrogate to estimate the effects of burning or mowing/haying on below-ground root biomass. Still other root biomass data were derived from studies where soil respiration measurements were taken from field plots that had been burned or hayed/mowed. Because roots are one of the major sources of carbon dioxide within the soil and serve to stimulate soil respiration, it can be an excellent surrogate for estimating changes in root system biomass. Measurements of soil respiration can therefore provide useful data relative to root biomass response to some type of disturbance.

Management and training impacts on below-ground biomass estimated from the metadata analysis were supplemented with impacts derived from field data. Fulton (2013) describes a 4-year field study at Fort Riley, KS that attempted to delineate the complex interactions between biomass and anthropogenic impacts including training and land management (i.e., burning and haying). A series of four 100 m x 100 m plots, created at two representative soil types for Fort Riley (clay upland loam soil and loam upland soils) (Figure 5), were divided into a modified 3<sup>2</sup> factorial design and subjected to a series of yearly land management and training impacts including light/heavy tracked vehicle impacts, controlled burning, and mowing/haying. Above and below-ground biomass samples were taken annually along with a set of soil moisture, strength, and condition parameter estimates.

A mixed linear model describing below-ground biomass estimates for each treatment condition was developed using the SAS Mixed Procedure (SAS Institute 2009). Estimates for each treatment condition were compared against the control condition (no land management or training impacts) to determine a percent increase or decrease from the control. The percent increase or decrease estimated by the treatment condition was then applied to the model by modifying the below-ground biomass according to the patch training and land management history.

Figure 5. Schematic illustrating Fort Riley land management/training impact study.



### 2.3.2 Land management and training impacts on above-ground biomass

The influence of land management and training on above-ground biomass was estimated from literature derived values and from the CENTURY model documentation. Conceptually, the above-ground biomass model was developed to represent the increase in production rate following biomass removal from burning or haying events due to increase in available

soil solar radiation (Knapp 1984). The above-ground biomass model removes a proportion of the above-ground biomass according to the combination of management or training activities. The rate of vegetation re-growth following the impact is then modified depending on the sites training and management history during the time period modeled. The rate of vegetation re-growth following the impact was estimated from Knapp et al. (1998) and Turner et al. (1993) for burning and haying, respectively.

### 2.3.3 Training attractiveness map

An approach developed by Guertin (2000) for Fort Hood estimated a probability surface that defines areas more likely to be impacted by training maneuvers. This approach is based on a logistic regression of observed disturbance data on a set of independent variables that appeared to influence training distribution (slope, vegetation type, installation region, and distance from maintained roads). Fang et al. (2002) performed an uncertainty analysis of the disturbance model developed by Guertin and concluded that error and uncertainty in the vegetation map were the dominant sources of mapping uncertainty. Fang et al. (2010) later employed this approach to identify areas more likely to be impacted by training maneuvers at Fort Riley, KS. This approach provides a better solution than assuming an even distribution across each training area.

A modified process based on the previously described logistic regression approach was taken to develop a training attractiveness map based on higher resolution, higher accuracy input data, including a 3m Digital Elevation Model (DEM) derived from Light Detection and Ranging (LIDAR) data and a vegetation map derived from aerial photography (Eq. (12)). This analysis used a set of independent variables proposed by Guertin (2000) and Fang et al. (2002) that were perceived to be important predictor variables for estimating the probability of disturbance, or “training attractiveness.” Land Condition-Trend Analysis (LCTA) data describing vegetation disturbance at Fort Riley from 1989–2001 were used as an observed disturbance dataset:

$$y = e^{(b_0 + \sum_{i=1}^7 b_i x_i)} \div 1 + e^{(b_0 + \sum_{i=1}^7 b_i x_i)} \quad (12)$$

Maximum disturbance recorded at 109 LCTA transects over this 13-year time period was used as the dependent variable in the logistic regression. Similar to previous studies, slope, vegetation type, installation region, and distance from maintained roads were determined for each LCTA plot loca-

tion using geospatial data layers and used as independent variables in the logistic regression model.

Mean slope and vegetation type was determined using a polygon representing a 30m buffer around each plot location. A low pass filter using a kernel size approximately the same size as the area of the buffer polygons was applied to the slope map derived from the 3m DEM to reduce local variation prior to extracting mean slope. Five dummy variables were used to represent four different landcover types (shrub, forest, tall grass and short grass) and one specific training region (central corridor) of the installation. Distance to paved roads and all roads were considered as explanatory variables, but similar to the results reported in Wang et al. (2010), distance to roads was not a significant predictor of training disturbance.

## **2.4 Model validation**

### **2.4.1 OPAL field data for treatment validation**

#### *2.4.1.1 Field data collection description*

Data from a 4-year field study at Fort Riley, KS were used as a validation of the training and land management impacts incorporated in the OPAL model. More specifically, this data allowed the testing of multiple land management and training scenarios at two locations within the area modeled on above- and below-ground biomass. Additional validation efforts described in Section 2.4.2 tested the ability of the model to accurately estimate above-ground biomass across the entire installation.

A series of four 100 m x 100 m plots were created at two representative soil types for Fort Riley (clay upland loam soil and loam upland soils) (Figure 5). These plots divided into a modified  $3^2$  factorial design and were subjected to a series of yearly land management and training impacts including light heavy tracked vehicle impacts, controlled burning, and mowing/haying. Above and below-ground biomass samples were taken annually along with a set of soil moisture, strength, and condition parameter estimates.

No above-ground biomass data from this study were used in the development of the algorithms incorporated in the OPAL model. However, due to the limited nature of below-ground biomass data, mean below-ground bi-

omass values were used to supplement the missing treatment impacts identified through the metadata analysis (described in Section 2.3.1). Since some of the below-ground biomass data were used in the model development, this is not a true validation of the below-ground biomass algorithms. However, this analysis will still provide an initial estimate of the ability for the OPAL model to estimate below-ground biomass given training and land management schedules.

#### *2.4.1.2 Treatment schedules*

The series of 100m x 100m plots were established in the spring of 2010. These plots were broken into sub-plots that were treated according to the 3<sup>2</sup> factorial design (Figure 5). Simulated vehicle training was performed with an M1A1 Abrams Main Battle Tank in the fall of 2010 and with a M88A2 Armored Recovery Vehicle in the spring 2012. Mowing/haying treatments were performed on the appropriate plots in September of 2010 and 2011. The controlled burn treatments were applied in the spring of 2011 and 2012. Additionally, at one site a wildfire burned the plots on 3 March 2012.

Management schedules were then created based on these actual treatment dates to simulate the impacts with the OPAL NetLogo model. Separate schedules were created for each unique treatment scenario (Table 2). Above- and below-ground biomass estimated values were exported to a GIS raster grid on the weeks when samples were obtained in the field (Weeks 23 and 29 in 2010, Week 27 in 2011, and Week 26 in 2012). The model was run for each of these scenarios from 2010–2012. Predicted values for each scenario were then compared with the field collected values from each corresponding plot.

#### **2.4.2 Fort Riley Range and Training Land Assessment (RTLA) above-ground biomass sampling data for spatial validation**

The approach described in Section 2.4.1 was used to assess the ability of the model to accurately predict above- and below-ground biomass given land management and training impacts. However, since the data used as the validation dataset were collected at only two locations, this approach does not assess how well the model spatially predicts vegetation conditions. Above-ground biomass data from 2010–2011 were obtained from the Fort Riley RTLA program. These data represent only the live vegetation component of the above-ground cover.

**Table 2. Training and land management treatment schedules modeled in the OPAL NetLogo model. The scenarios exactly match the dates the field plots were treated.**

Treatment	Plot	Track2010	Track2012	Mow2010	Mow2011	Burn2010	Burn2011	Burn2012
		Date	Date	Date	Date	Date	Date	Date
Control_Burned	BB	NA	NA	NA	NA	NA	4/22/2011	3/3/2012
Control_Burned	EE	NA	NA	NA	NA	NA	5/15/2011	4/21/2012
Control_Control	BB	NA	NA	NA	NA	NA	NA	3/3/2012
Control_Control	BB	NA	NA	NA	NA	NA	4/22/2011	3/3/2012
Control_Control	EE	NA	NA	NA	NA	NA	NA	NA
Control_Mowed	BB	NA	NA	9/28/2010	9/30/2011	NA	NA	3/3/2012
Control_Mowed	BB	NA	NA	9/28/2010	9/30/2011	NA	4/22/2011	3/3/2012
Control_Mowed	EE	NA	NA	9/28/2010	9/30/2011	NA	NA	NA
Track Heavy_Burned	BB	10/27/2010	3/27/2012	NA	NA	NA	4/22/2011	3/3/2012
Track Heavy_Burned	EE	10/27/2010	3/27/2012	NA	NA	NA	5/15/2011	4/21/2012
Track Heavy_Control	BB	10/27/2010	3/27/2012	NA	NA	NA	4/22/2011	3/3/2012
Track Heavy_Control	BB	10/27/2010	3/27/2012	NA	NA	NA	NA	3/3/2012
Track Heavy_Control	EE	10/27/2010	3/27/2012	NA	NA	NA	NA	NA
Track Heavy_Mowed	BB	10/27/2010	3/27/2012	9/28/2010	9/30/2011	NA	4/22/2011	3/3/2012
Track Heavy_Mowed	BB	10/27/2010	3/27/2012	9/28/2010	9/30/2011	NA	NA	3/3/2012
Track Heavy_Mowed	EE	10/27/2010	3/27/2012	9/28/2010	9/30/2011	NA	NA	NA
Track Light_Burned	BB	10/27/2010	NA	NA	NA	NA	4/22/2011	3/3/2012
Track Light_Burned	EE	10/27/2010	NA	NA	NA	NA	5/15/2011	4/21/2012
Track Light_Control	BB	10/27/2010	NA	NA	NA	NA	4/22/2011	3/3/2012
Track Light_Control	BB	10/27/2010	NA	NA	NA	NA	NA	3/3/2012
Track Light_Control	EE	10/27/2010	NA	NA	NA	NA	NA	NA
Track Light_Mowed	BB	10/27/2010	NA	9/28/2010	9/30/2011	NA	4/22/2011	3/3/2012
Track Light_Mowed	BB	10/27/2010	NA	9/28/2010	9/30/2011	NA	NA	3/3/2012
Track Light_Mowed	EE	10/27/2010	NA	9/28/2010	9/30/2011	NA	NA	NA

Training and land management schedules obtained from Fort Riley were used to create scenarios for simulation with the model. The land management scenarios were created from actual controlled and wildfire burn maps and the hay leasing database map. Section 2.2.2.3 describes the development of training and land management simulation schedules based on the actual management databases. The above-ground biomass estimates at the sampling dates were then exported for comparison with the 58 composite above-ground biomass observations across the installation from the 2 years.



## 3 Results and Discussion

### 3.1 Calibration Results

#### 3.1.1 Land management and training impacts on above- and below-ground biomass

A metadata analysis was performed to estimate below-ground biomass dynamics in response to disturbances such as surface perturbation (military training), burning, and haying/mowing in tallgrass prairie ecosystems. The treatments included in the analysis included three levels of disturbance/impact (control, light, heavy) in a factorial arrangement with three types of management practices (control, burning, haying). The analysis was focused on obtaining biomass responses for the Tallgrass, Flinthills, or Konza Prairie ecosystems. Table 3 lists the results of the comprehensive literature review of available sources, seasons, and years.

Data in Table 3 are expressed as percent increase or percent decrease in root biomass when compared to the specific impact and/or management practice control and are from Tallgrass, Flinthills, or Konza Prairies unless otherwise noted. This exercise served to capture the significant expected variability in root biomass due to differences in soil types, precipitation amounts, level and seasonality of disturbance, and plant community composition. Data in Table 3 reflect a combination of values derived from field studies involving directly collected root biomass, microbial biomass, or soil respiration. Treatments consist of three levels of disturbance/impact (control, light, heavy) in a factorial arrangement with three types of management practices (control, burning, and haying/mowing). Note: some disturbance/impact:management practice combinations do not have root biomass values associated with them due to the inability to locate data specific to these combinations. The manuscripts referenced in Table 3 provide more information regarding these data and how they were acquired.

**Table 3. Root biomass expressed as percent increase or percent decrease in root biomass when compared to the specific impact and/or management practice control.**

Change	Notes	Source
<b>1) No Impact x No Management</b>		
NA		
<b>2) No Impact x Burning</b>		
+25%	In spring	Johnson and Matchett (2011)
+15%	In spring	Tufekcioglu et al. (1999)
-15%	In summer	Heath (1985)
+40%	Initially, but declines with increasing fire frequency	Ojima et al. (1994)
-1 to 2%	Per year if burned annually	Ojima, (1987)
-3 to 5%	If followed by dry (50–75% of avg ppt) summer	Garcia et al. (1994)
+5 to 8%	If followed by wet (125–150% of avg ppt) summer	Garcia et al. (1994)
+1%		Benning and Seastedt (1997)
+48%		Kitchen et al. (2009)
+7%		Gibson et al. (1993)
+22%		Kucera and Dahlman (1968)
+68%		Kucera and Dahlman (1968)
+3%		Bremer et al. (2002)
+7%		Mielnick and Dugas (2000)
+102%		Collins (1987)
+33%		Collins (1987)
+6%		Callaham et al. (2003)
<b>3) No Impact x Haying/Grazing</b>		
-20%	In short and mixed grass prairies	Richards et al. (1984)
-30%	In short and mixed grass prairies	Detling et al. (1984)
-18%	In spring/summer	Vogel and Moser (1982)
-22%	In summer/fall	Vogel and Moser (1982)
-16%	In mixed grass prairie	Biondini et al. (1998)
-15%	If followed by dry (50–75% of avg ppt)	Fiala et al. (2009), Gwyer et al. (1996)
-11 to -18%	In summer	Garcia et al. (1994), Garcia (1992)
-2%		Benning and Seastedt (1997)
+7%		Kitchen et al. (2009)
-17%		Gibson et al. (1993)
-28%		Todd et al. (1992)
-17%		Bremer et al. (1998)
-15%		Wilsey et al. (1997)
-8%		Bremer et al. (2002)
+11%		Collins (1987)
-20%		Collins (1987)
-33%		Callaham et al. (2003)
-14 to -33%	As defoliation frequency increases from 1 to 5	Engel et al. (1998)
-30%		Polley and Detling (1989)

Change	Notes	Source
<b>4) Light Impact x No Management</b>		
NA		
<b>5) Light Impact x Burning</b>		
NA		
<b>6) Light Impact x Haying/Grazing</b>		
NA		
<b>7) Heavy Impact x No Management</b>		
-45%	In shortgrass prairie scraping experiments	Williams and Munns (1979)
<b>8) Heavy Impact x Burning</b>		
NA		
<b>9) Heavy Impact x Haying/Grazing</b>		
-65%	In shortgrass prairie experiments	Williams and Munns (1979)

In some instances, the study reported the specific parameters for which the below-ground biomass response was documented. For example, Garcia et al. reported a 5–8% increase in below-ground biomass in response to controlled burning when followed by a wet summer (i.e., 125–150% of average precipitation), but documented a 3–5% decreases in below-ground biomass when the burn was followed by a dry summer (i.e., 50–75% of average precipitation). In this instance, these differences reflect the ability for above-ground vegetation and cover to preserve soil moisture in dry conditions. In wet years, the extra cover experienced in the unburned plot decreased productivity by reducing sunlight and decreasing initial soil temperatures. However in dry years when soil moisture was scarce, the same cover preserved soil moisture, which increased overall productivity.

While these effects are obviously important to an explanation of the dynamics of the soil-vegetation systems, an attempt to generalize these results was made for modeling purposes. While this generalization may reduce accuracy on a case-by-case basis, by incorporating the body of observations the model should improve its overall accuracy over a large number of years and over a larger area. Table 4 lists the distribution of below-ground biomass responses described for burning and haying treatments; Figure 6 shows the observed trends. This analysis was only performed on the Burning and Haying/Grazing vs. Control conditions as these were the only treatments with a large number of observations (literature derived biomass responses).

Table 4. Summary statistics of below-ground biomass responses to burning and haying/grazing.

Statistic	Burning vs. Control	Haying/Grazing vs. Control
Number of samples	17	19
Mean (% Increase or Decrease)	21.4	-15.2
Variance	877.1	183.2
standard dev (%)	29.6	11.8

Figure 6. Distribution of percent change in below-ground biomass derived from literature to illustrate the uncertainty and variability below-ground biomass response to management regimes.

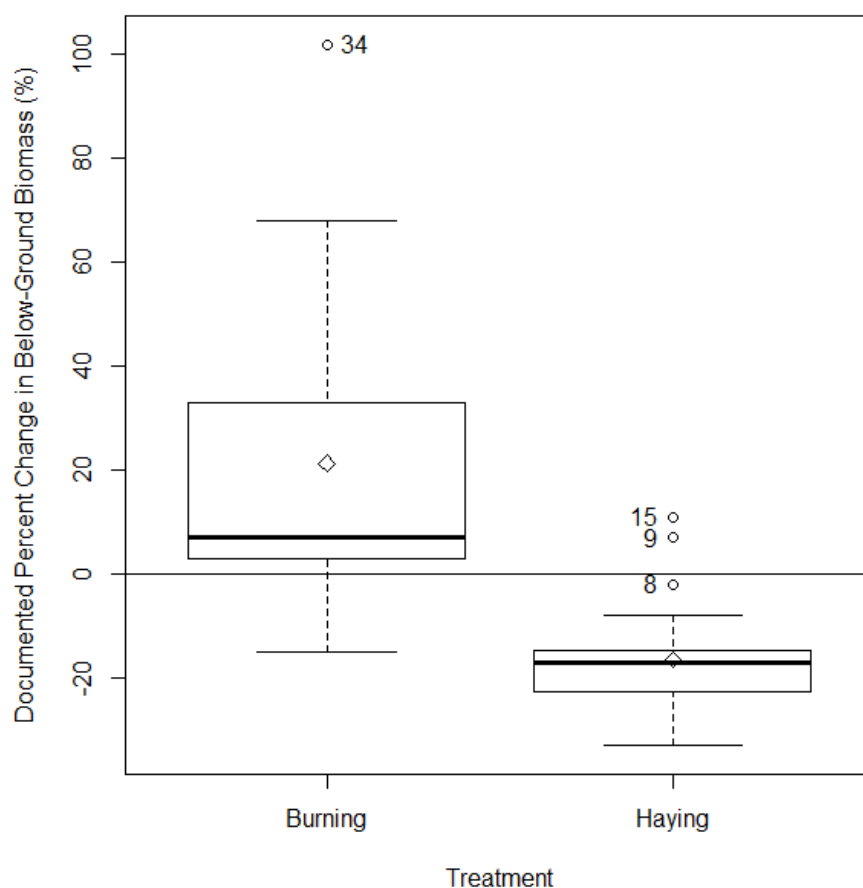


Figure 6 shows the general range and frequency of observations found in literature. Across 19 studies, haying/grazing reduced below-ground biomass compared to the control condition by an average of 15.2%. The standard deviation was 11.8%. Burning on the other hand, increased the below-ground biomass by an average of 21.7% with a standard deviation of 29.6%. This reflects the large differences in response due to burning timing or frequency and soil moisture conditions.

While this approach estimates the general response in below-ground biomass due to haying and burning treatments, the literature review did not identify studies that had investigated all of the treatment combinations required for the model. These values were supplemented by below-ground biomass responses observed in the Fort Riley plot study (Fulton 2013). Figure 7 shows the below-ground biomass estimates of the mixed linear model created based on the field data. The treatments are named by land management treatment + training treatment. The land management treatments are control (CTRL), burning (BURN), and mowing (MOW). The training treatments are no training (CTRL), light tracking (LT), two light tracking treatments in consecutive years (LT+L), and light tracking followed by a year of recovery (LT+R).

An increase or decrease factor was then calculated by adding the percent change from the CTRL+CTRL condition to 1 (Figure 8). For example, to estimate the below-ground biomass for each management-training condition, multiply the condition factor by control condition. The treatments are named by the convention defined above. This provides a change factor that could be multiplied by the control condition in the model to estimate the treated pixel. These change factors supplemented the missing biomass responses identified in the metadata analysis.

Figure 7. Below-ground biomass estimates given management/training scenario from Fort Riley plot data (Fulton 2013). The error bars represent the standard deviation of the estimate.

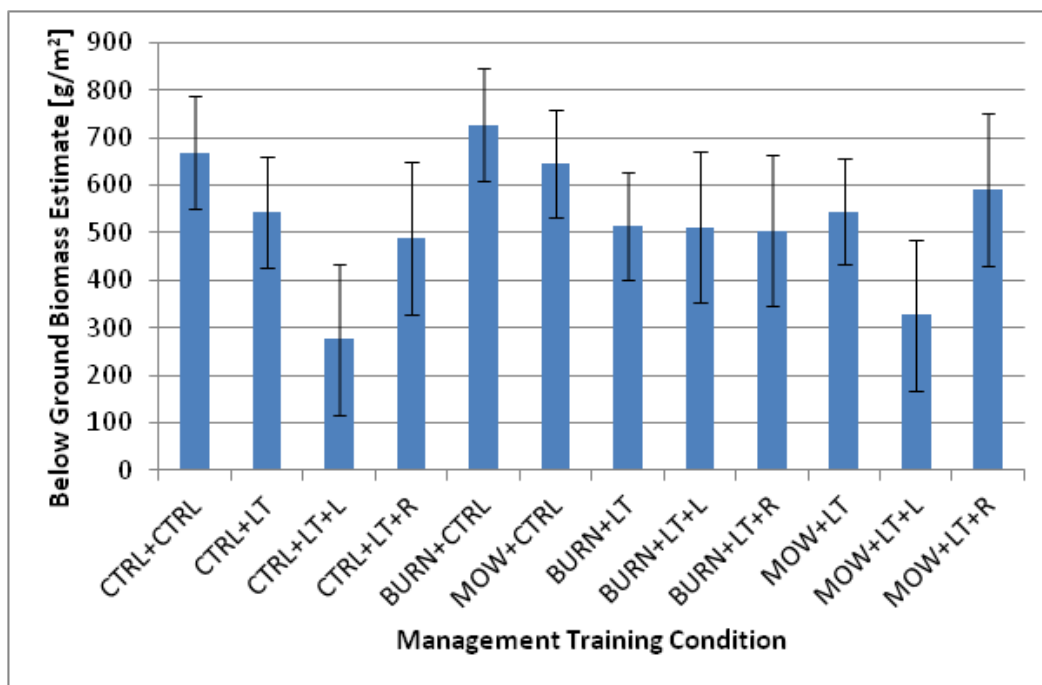
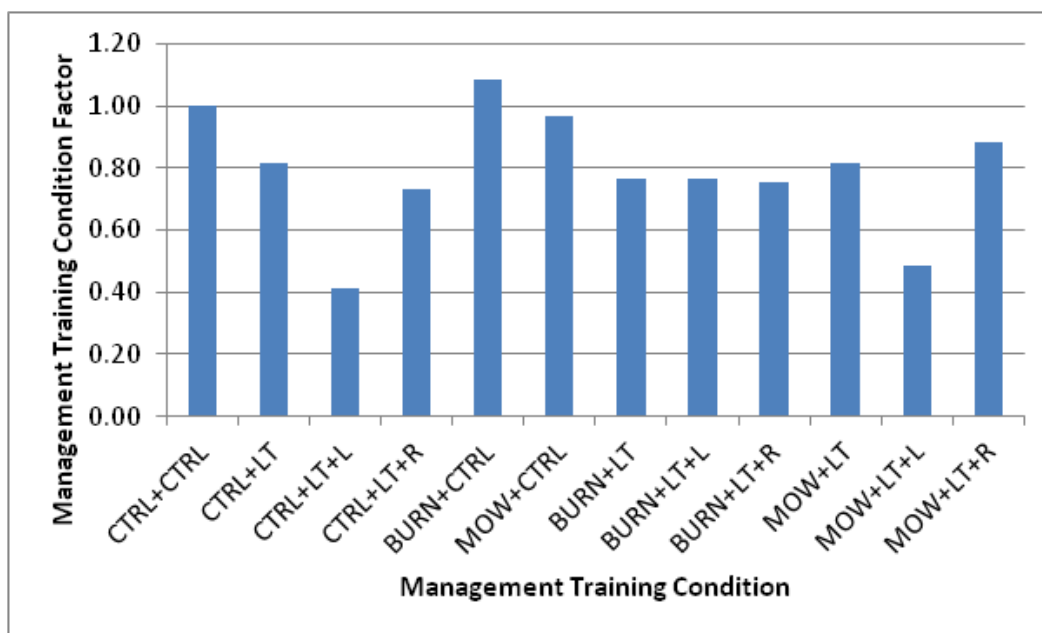


Figure 8. Below-ground biomass condition factors estimated from Fort Riley plot data (Fig. 7).

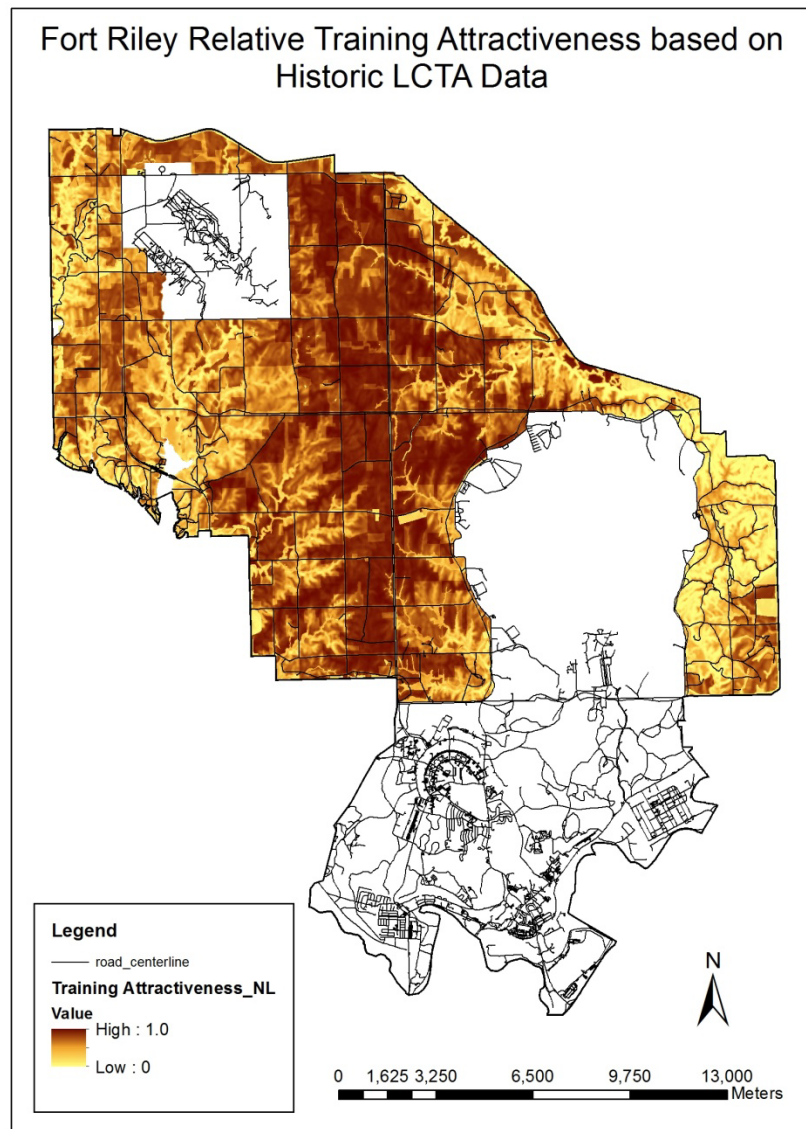


Above-ground biomass responses to burning and haying were estimated from the literature. Knapp et al. (1998) reported a mean annual productivity of 527.5 g/m<sup>2</sup> with annual burns and 406.7 g/m<sup>2</sup> with no burn. Since the model requires a weekly rate, the difference was divided by the number of weeks after burning reported in the paper. This resulted in an 8.29 g/m<sup>2</sup> increase in production per week following a burning event. Turner et al. (1993) reported a mean yearly above-ground production of 544 g/m<sup>2</sup> with one mowing event and 450 g/m<sup>2</sup> for the control condition (no mowing). Using the same methods as the burning calculation, this resulted in a 1.8 g/m<sup>2</sup>/week increase in above-ground biomass due to haying. While the difference between treatments and controls were similar, the time between treatment and sampling was much larger for the haying study resulting in the lower weekly rate. While this method provides estimates for the change in biomass growth, the overall approach is highly dependent on the timing between treatments and sampling. Over an entire year, this approach likely overestimates the response due to treatment while it likely underestimates the response due to treatment in a shorter time-scale.

### 3.1.2 Training attractiveness map

A procedure modified from previous work (Guertin 2000, and Fang et al. 2002) was performed to create a layer depicting the relative frequency training land would be used based on historic LCTA data (Figure 9).

Figure 9. Map of Fort Riley's relative training attractiveness based on LCTA data from 1989–2001. Note: Darker colors indicate areas more likely to be used for training based on historic data. White areas were not included in the estimation as the areas depict impact areas or installation cantonment.



The overall model had good agreement with the field disturbance data with the model predicting 61% of the variation ( $R^2 = 0.61$ ) in observed disturbance. The model found that mean slope and installation region (within vs. outside the central corridor) were significant in predicting disturbance patterns (Table 5). Additional variables related to vegetation type were not significant, but were retained in the final model based on knowledge of their influence on training preferences at Fort Riley, KS

Table 5. Predictive disturbance model parameter estimates.

Parameter	Estimate	p-value
$b_0$	-1.60242	0.5734
$b_1$	-0.21104	0.0001
$b_2$	1.665222	0.8768
$b_3$	1.569357	0.5846
$b_4$	2.612649	0.3594
$b_5$	3.135057	0.2719
$b_6$	1.024429	<0.0001

Previous attempts to estimate disturbance patterns using a predictive model accounted for 46% of the spatial variation in observed disturbance at Fort Hood, TX (Fang et al. 2002). Fang et al. (2007) later introduced interaction terms between dependent variables and demonstrated that the type and amount of input data affected model predictions, which predicted from 39 to 54% of observed disturbance at Fort Hood, TX. Wang et al. (2010) applied a similar approach for predicting the spatial variation of disturbance at Fort Riley, KS using 90m spatial resolution geospatial data. Predictive models were developed annually from 1989–2001 with models accounting for 34 to 57% of the spatial variation in observed disturbance. The slight improvement in predictive capability of the current model is likely due to the improved spatial resolution of the DEM derived from LIDAR, which was used to assess slope as a predictive variable.

Overall, the training attractiveness layer seems to match how the training lands have typically been used. For example, the dark area down the center of the installation has historically been an area with high training intensity. However, with the new Digital Multi-Purpose Range Complex (DMPRC), the safety fan now includes much of the training areas south-east of the range, which will significantly reduce the training loads in this area. The historic LCTA data would not reflect this change. In consideration of this, and for the purposes of this model, training is still allocated according to RFMSS-based training areas and is then divided among the area according to the training attractiveness map so this overall change in training areas used will not have a large impact.



## 3.2 Validation results

### 3.2.1 Comparison against OPAL field data

#### 3.2.1.1 Above-ground biomass validation

Data from a 4-year field study at Fort Riley, KS were used to validate the training and land management impacts incorporated in the OPAL model. These data allowed the testing of multiple land management and training scenarios at two locations within the area modeled on above- and below-ground biomass. The treatment schedules for the field study were used to develop the impact scenarios in the model simulation as discussed in Section 2.4.1.2. This validation section groups the results of both the model and field collected values by land management treatment and vehicle training treatment. The results are illustrated with both boxplots and scatterplots.

Figure 10 shows the predicted and measured above-ground biomass values grouped by land management treatment. Plot 10a illustrates that the model predicted little difference in the above-ground biomass under the different land management scenarios tested with mean values across all plots of 286.8, 292.7, and 306.1 g/m<sup>2</sup> for burn, control, and mow treatments, respectively. However, the measured above-ground biomass values for the treatments were 543.8, 264.5, and 344.2 g/m<sup>2</sup> for burn, control, and mowed treatments, respectively. While the mowing and control predictions were fairly accurate, the burn treatment prediction average was approximately 250 g/m<sup>2</sup> lower than the measured values.

The reason the predicted values are so much lower than the measured values is because this prediction uses an increase in growth/week for burned conditions. However, it appears that, even with this increased growth rate (+8 g/m<sup>2</sup>/week), the biomass is still not increasing to amounts greater than that removed in the time between burning and sampling. Over larger time intervals, the burned plots would increase above the control due to the increased growth rate. One solution would be to just base the burned plot AGB on a percent increase over a controlled condition. Another would be to develop a growth rate function that is much larger than g/m<sup>2</sup>/week initially and then to reduce the growth rate later. However, without firm biomass growth data, many assumptions would be required to estimate that function.

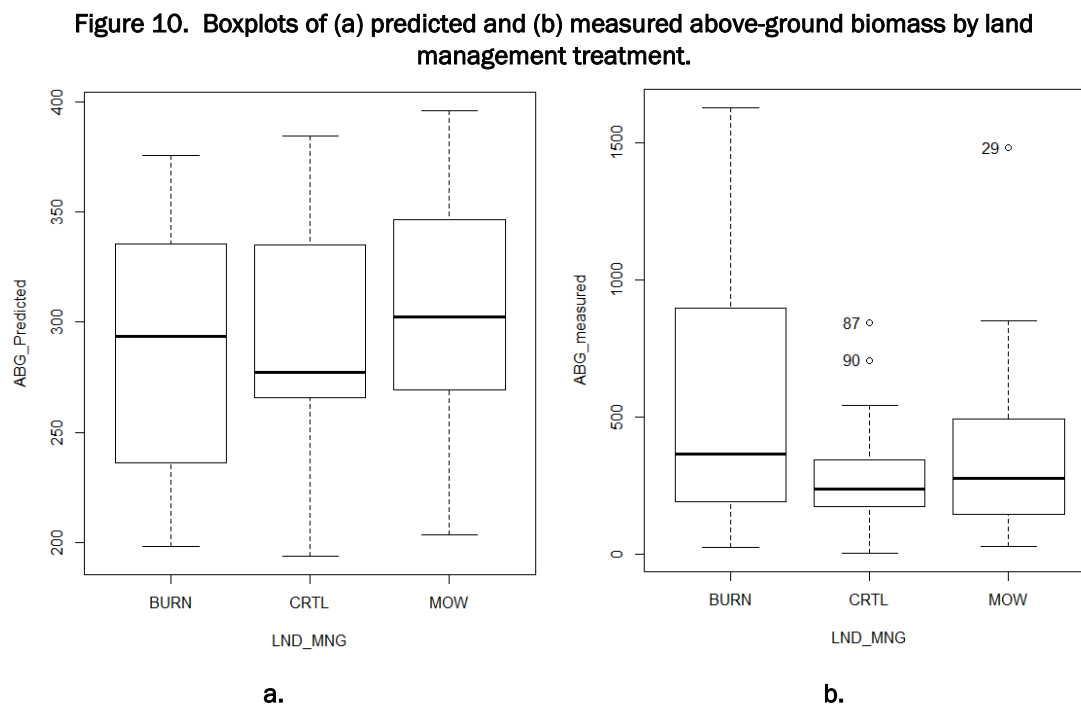


Figure 11 shows the scatterplot of predicted vs. measured points. As illustrated, the model was not capable of predicting some of the extreme values observed in the burning treatment. In certain instances, the measured above-ground biomass was greater than 1500 g/m<sup>2</sup> while the maximum predicted value was only around 375 g/m<sup>2</sup>. This could be a function of the burn and sampling timing in the field study. As described in Section 2.3.2, **by assuming a constant weekly increase (or decrease) in treatments based on a yearly average observation, the model is not as sensitive to land management treatments in the short-term, but is more sensitive to treatments in longer time-scales.** Since the interval between burning and sampling in the field study was less than 2 months, the increase in growth rate according to the annual increase still did not increase the above-ground biomass amount compared to the control condition due to the loss of biomass during the burning event.

Figures **Error! Reference source not found.a** and **Error! Reference source not found.b**, respectively, show the predicted and measured above-ground biomass grouped by training treatment. The mean above-ground biomass values were 293.5, 345.7, 236.4, and 256.1 g/m<sup>2</sup>, respectively, for the control (CTRL), 1 year light traffic (LT), 2 years of repeated light traffic (LT+LT), and 1 year of light traffic followed by 1 year of recovery (LT+R). The measured values for these same treatments were 552.9, 327.6, 74.6, and 325.4 g/m<sup>2</sup> respectively.

Figure 11. Scatterplot of predicted vs. measured above-ground biomass by land management treatment.

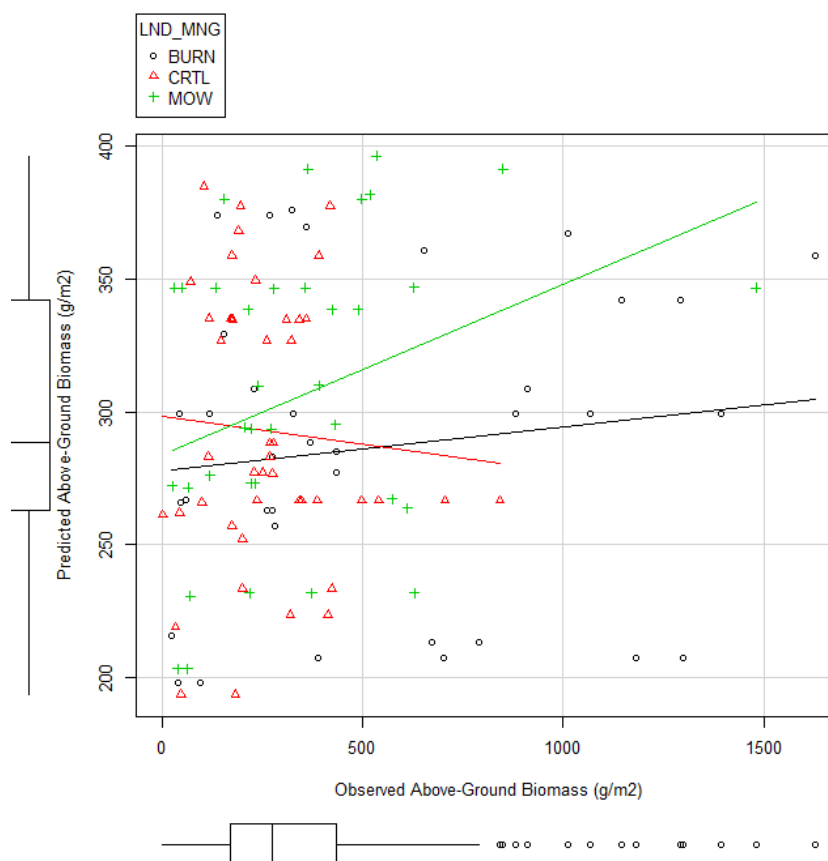
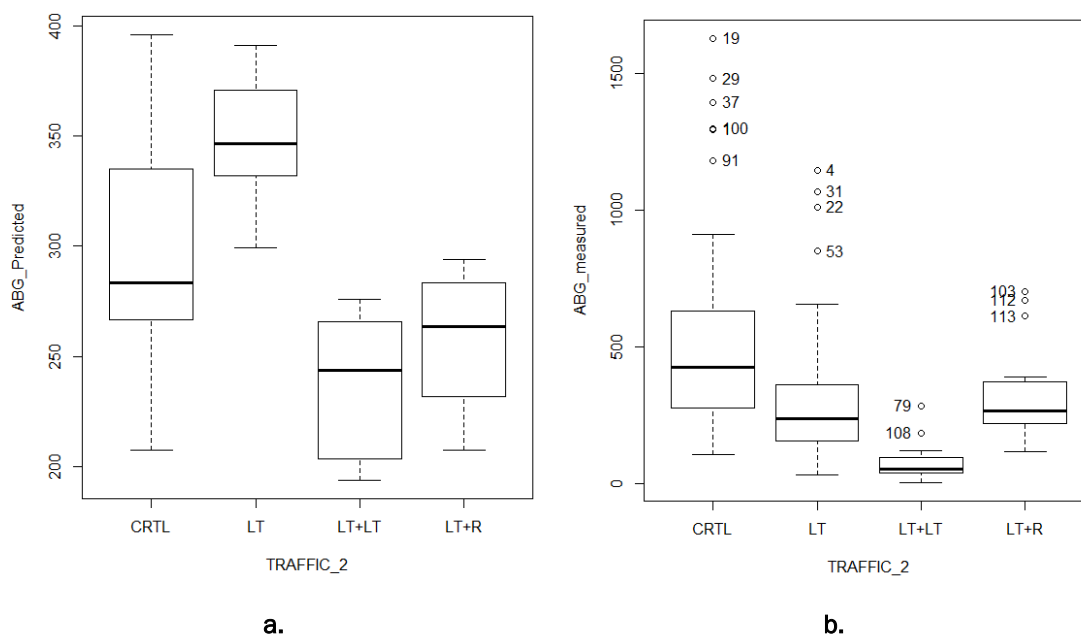


Figure 12. Boxplots of (a) predicted and (b) measured above-ground biomass by training treatment.



Due to the field study design, the LT treatment was measured only in 2011, whereas the LT+LT and LT+R treatments were measured in 2012. The CRTL treatment was measured in both 2011 and 2012. Figure 13a shows the above-ground biomass by year. The moisture or temperature conditions in 2012 limited the simulated vegetation production compared with the previous year. This is observed slightly in the field data (Figure 13b), but not to the same extent.

Since the LT treatment was conducted only in 2011, this results in a higher above-ground biomass compared with the other treatments in the model results. However, despite the explanation for this increase in above-ground biomass in the LT the same trend should be apparent in the measured data. Comparison between the two datasets indicates **the model underestimates the impact of training on the above-ground biomass**. This is apparent in the change in biomass from the CRTL to LT+LT of 478.3 g/m<sup>2</sup> in the field data. This difference was only 57 g/m<sup>2</sup> in the model results. This indicates the training impact outweighed the differences between years in the field data while the differences in years outweighed the training impact in the model results.

Figure 13. Boxplots of (a) predicted and (b) measured above-ground biomass by training treatment.

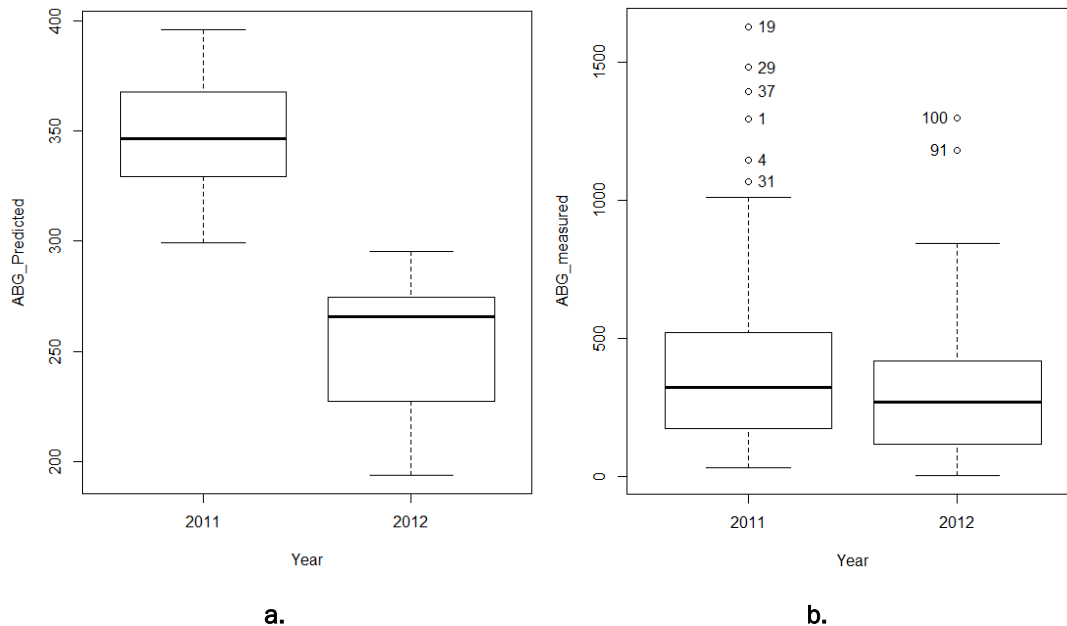


Figure 14 and the described land management treatment effects on above-ground biomass both show that the model does not predict the extreme above-ground biomass measurements observed in the field. A histogram of the absolute value of the error between the measured and predicted values was created to illustrate the ability for the model to accurately predict the measured values (Figure 15). Again, this figure indicates there are certain conditions that result in high observed above-ground biomass measurements that are not accounted for in the model. Generally, **the model tended to predict above-ground biomass values lower than the observed field plot data**. The field study collected all cover within a 0.25 m<sup>2</sup> frame while the model only predicts live vegetation cover. This would result in an underestimation of above-ground biomass compared with the field data.

Figure 14. Scatterplot of predicted vs. measured above-ground biomass by training treatment.

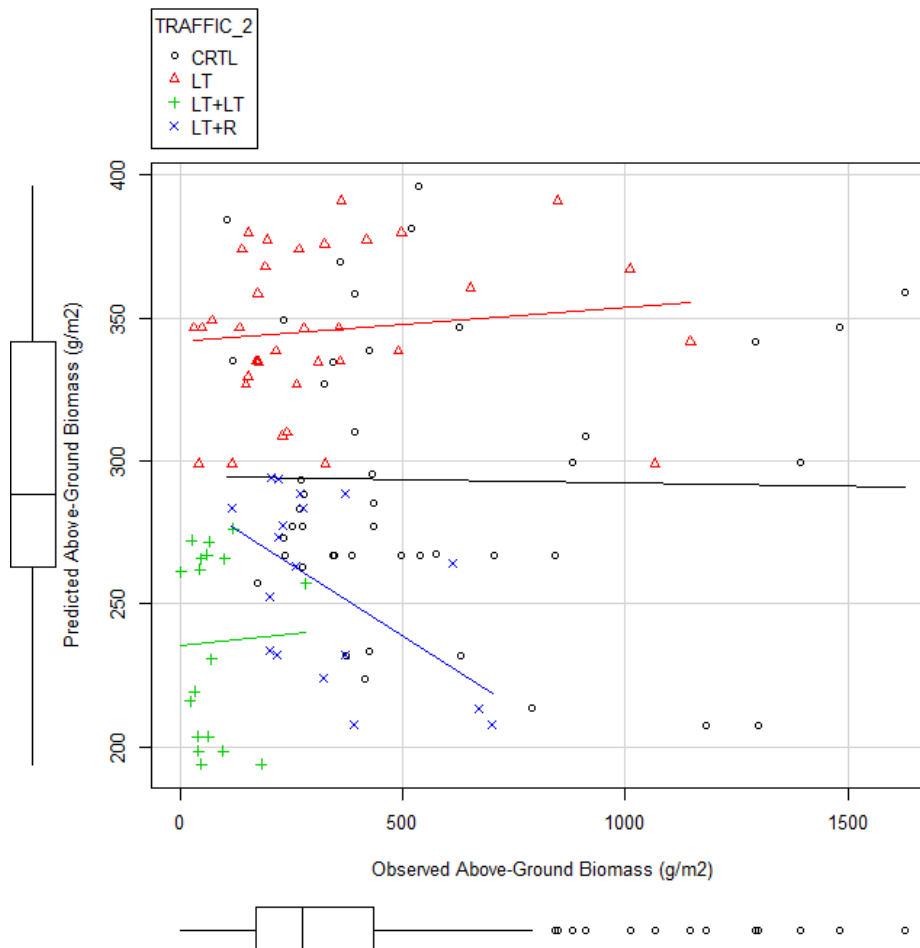
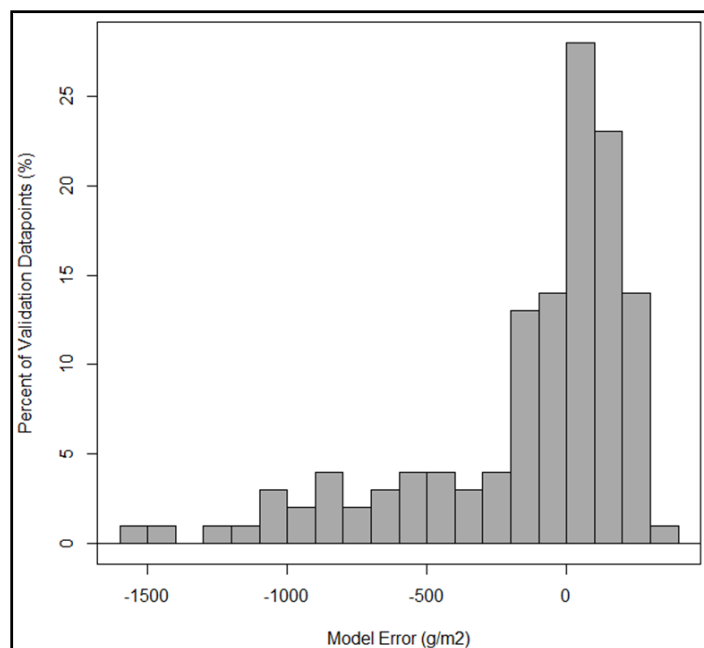


Figure 15. Histogram of model-predicted above-ground biomass error compared to measured above-ground biomass.

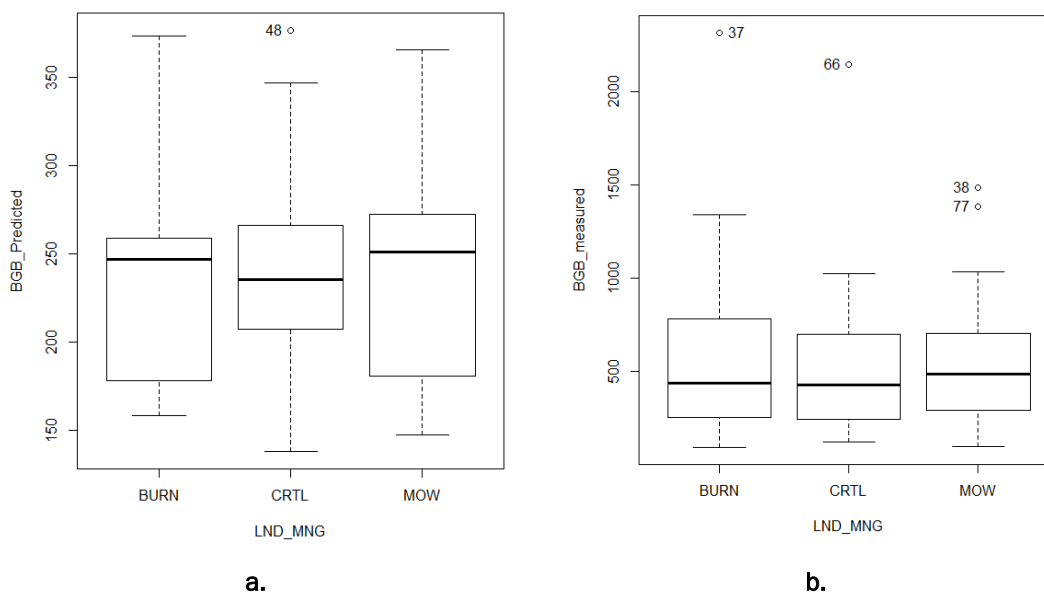


#### 3.2.1.2 Below-ground biomass validation

Below-ground biomass data from the same 4-year field study at Fort Riley, KS were used to test the accuracy of the model in predicting below-ground biomass responses to training and land management treatments. As discussed in the methods section, since the differences between treatments in the below-ground biomass data were used in the development in some of the model components, this is not a true validation. The treatment schedules for the field study were used to develop the impact scenarios in the model simulation as discussed in Section 2.4.1.2. Figure 16 shows the predicted and measured below-ground biomass results. The field data resulted in no significant difference between treatments. This was also observed in the model-predicted data. As in the case of above-ground biomass, the model-predicted values (average = 240.7 g/m<sup>2</sup>) were lower than the field observations (average = 549.2 g/m<sup>2</sup>).

As below-ground biomass is predicted in the model based on a root-to-shoot ratio, this would be expected based on the above-ground biomass error. As discussed in Fulton (2013), **there are few observed differences in below-ground biomass between land management treatments over the study in both the predicted and observed data.** This is due in part to the short duration of the study relative to the time-scale of below-ground biological processes.

Figure 16. Boxplots of (a) predicted and (b) measured below-ground biomass by land management treatment.



When grouped by vehicle training treatments, differences between treatments are apparent (Figure 17). The mean model-predicted below-ground biomass values by treatment are 270.1, 265.8, 163.3, and 179.6 g/m<sup>2</sup>, respectively, for the CRTL, LT, LT+LT, and LT+R treatments. These same treatments resulted in mean observed below-ground biomass values of 628.0, 534.3, 371.6, and 528.5 g/m<sup>2</sup>, respectively. While the same trends in impacts are observed, the LT treatment is slightly elevated compared with the control due to the differences in yearly conditions as discussed with above-ground biomass.

Figures 17 and 18 show plots of the predicted vs. observed below-ground biomass values. The range in model-predicted values is only 239 g/m<sup>2</sup> while it is around 1400 g/m<sup>2</sup> (excluding two outliers) for the observed data. **While the below-ground biomass model adequately predicts the trends between treatments, it is not nearly sensitive enough to predict the wide range in values in the observed data** (Figure 18). The model includes a productivity index given in the USDA soil survey. Other possible variables that could be incorporated in the model to increase the sensitivity of the model to actual conditions are soil nutrient levels, a higher resolution soil moisture model, plant species data, slope, and aspect. **Across all samples, the model predicted below-ground biomass ~300 g/m<sup>2</sup> below observed values** (predicted mean = 241.8 g/m<sup>2</sup>, observed mean = 545.3 g/m<sup>2</sup>, see Figure 19). This is also observed in the histogram of model error (Figure 20).

Figure 17. Scatterplot of predicted vs. measured below-ground biomass by land management treatment

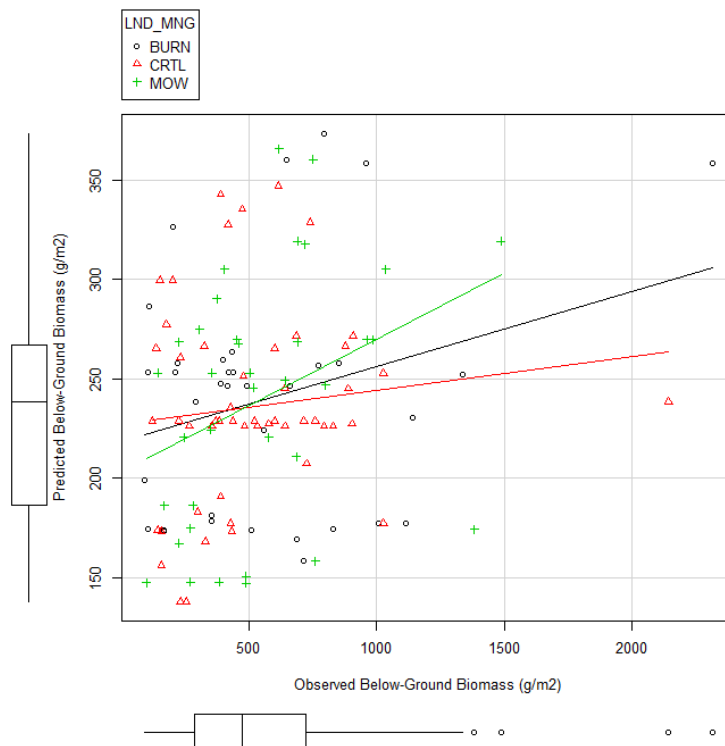


Figure 18. Scatterplot of predicted vs. measured below-ground biomass by training treatment.

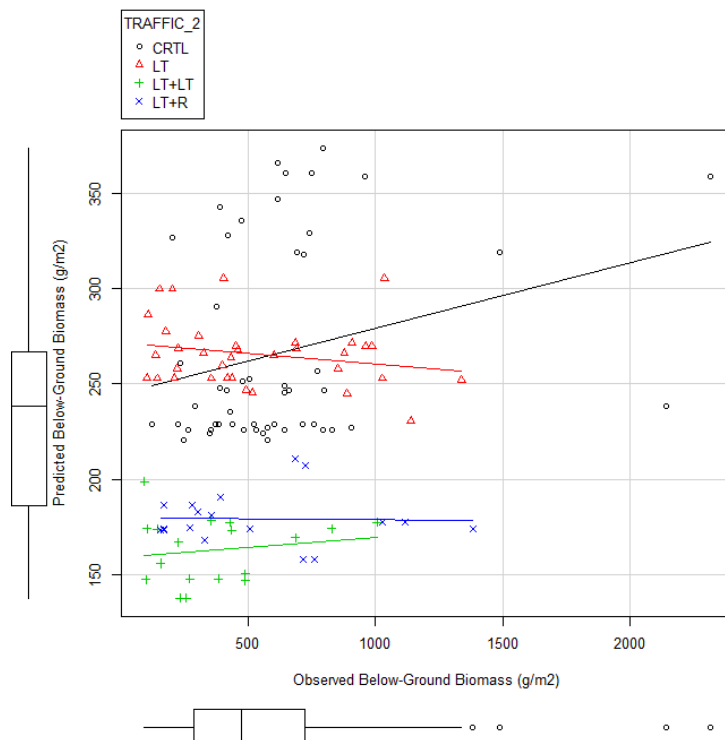




Figure 19. Boxplots of (a) predicted and (b) measured below-ground biomass by training treatment.

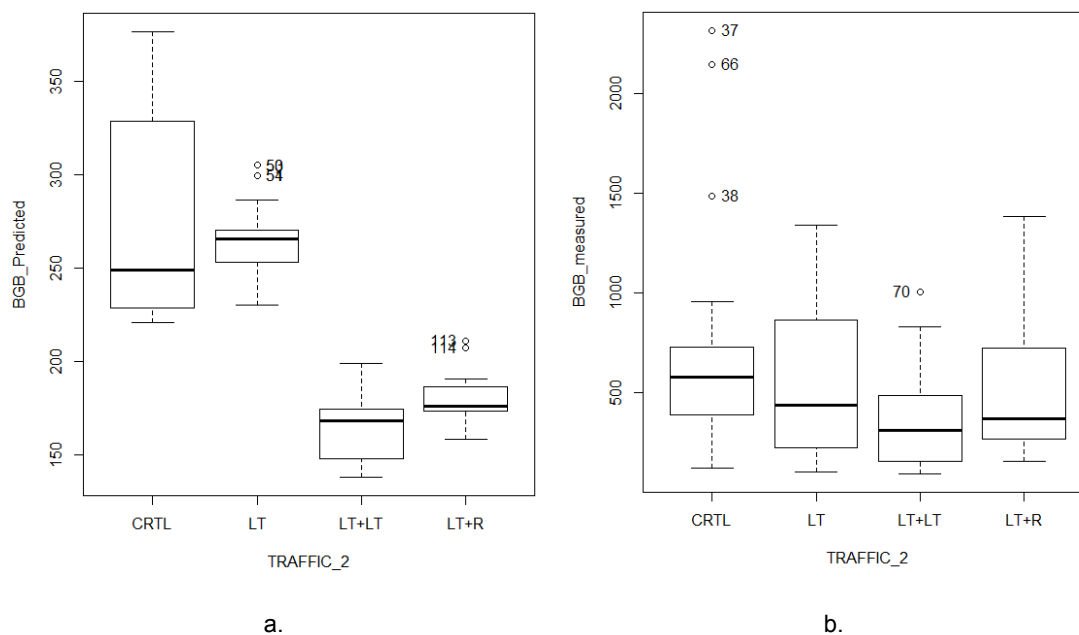
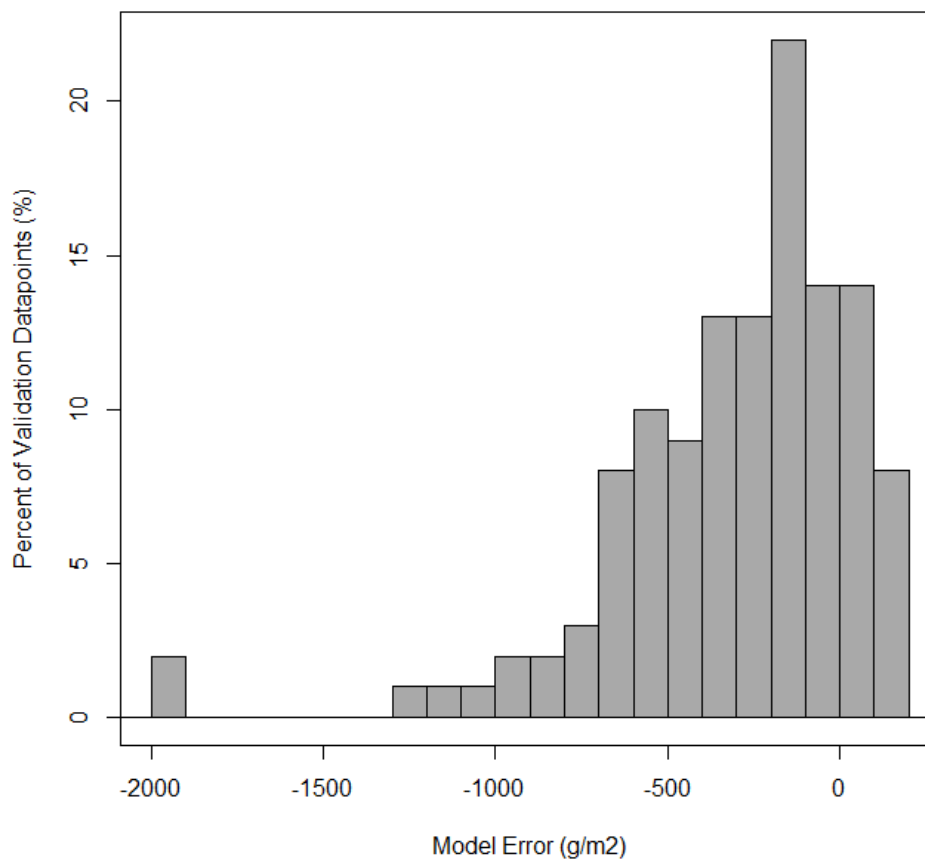


Figure 20. Histogram of model-predicted below-ground biomass error compared to measured below-ground biomass.



### 3.2.2 Comparison with Fort Riley ITAM historic above-ground biomass data.

While the validation discussed in the previous section tested the accuracy of the model in predicting land management and training impacts on above- and below-ground biomass, it did not test the ability of the model to predict biomass across a large spatial area. Additionally, the field plot data included all above-ground cover, while the model only predicts live vegetation. This partially explains the lower biomass rates predicted by the model compared with the field data.

Above-ground biomass clipping data from 2010–2011 were obtained from the Fort Riley RTLA program. These data represent only the live vegetation component of the above-ground cover. Each of the 58 data points is a composite sample that reduces some of the variability observed in the measured data from the field plots. Training and land management schedules obtained from Fort Riley were used to create scenarios for simulation with the model. The land management scenarios were created from actual controlled and wildfire burn maps and the hay leasing database map.

Figure 21 shows a plot of the predicted vs. measured values for 2010–2011. The mean model-predicted above-ground biomass across all sample sites was 402.1 g/m<sup>2</sup> with a standard deviation of 80 g/m<sup>2</sup>. The mean measured above-ground biomass across all above-ground composite samples was 308.6 g/m<sup>2</sup> with a standard deviation of 61.3 g/m<sup>2</sup> resulting in a mean model error of 93.5 g/m<sup>2</sup>. This is also observed in the histogram of model error Figure 22. **While the model-predicted values smaller than observed values compared the OPAL field plot data, it predicted values slightly larger than the Fort Riley RTLA plot data from 2010–2011.**

The **correlation coefficient between measured and predicted above-ground biomass was 0.34** (Table 6). Fort Riley RTLA creates a calibrated biomass image from the sampling date based on a regression between Normalized Difference Vegetation Index (NDVI) and the RTLA above-ground biomass used for this validation effort. The correlation between biomass values based on the NDVI correlation and the actual measured data is only slightly higher (0.41 compared to 0.34) than the model-predicted values. This indicates that the variability in above-ground biomass observed across the landscape is difficult to quantify, even with a high resolution remote sensed image.

Figure 21. Scatterplot of predicted vs. measured above-ground biomass from 2010–2011 compared with Fort Riley RTLA data.

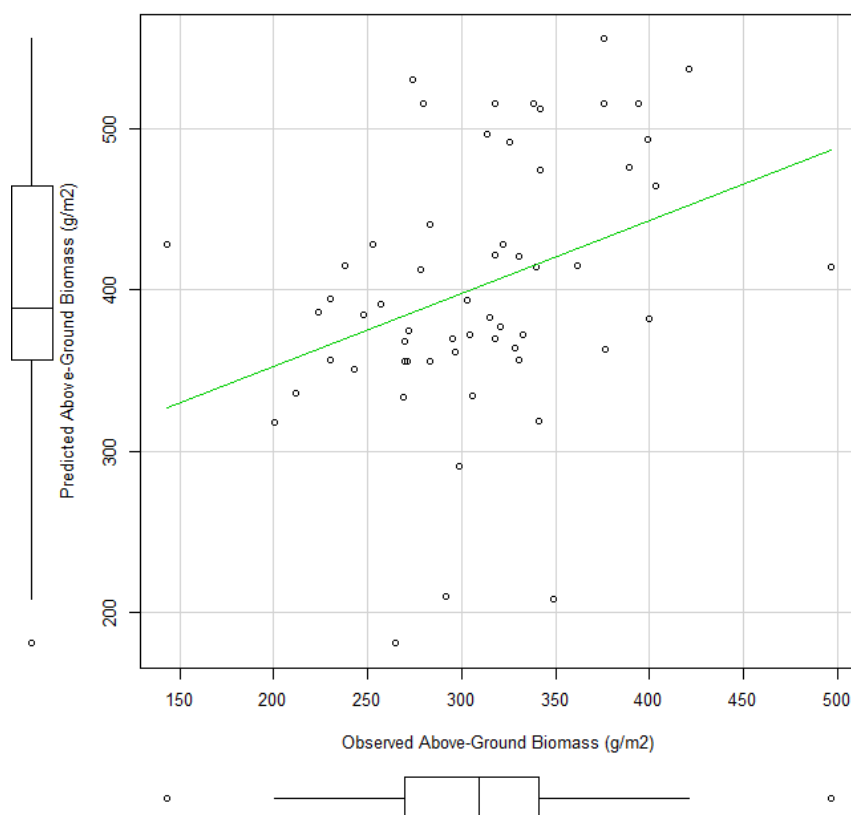
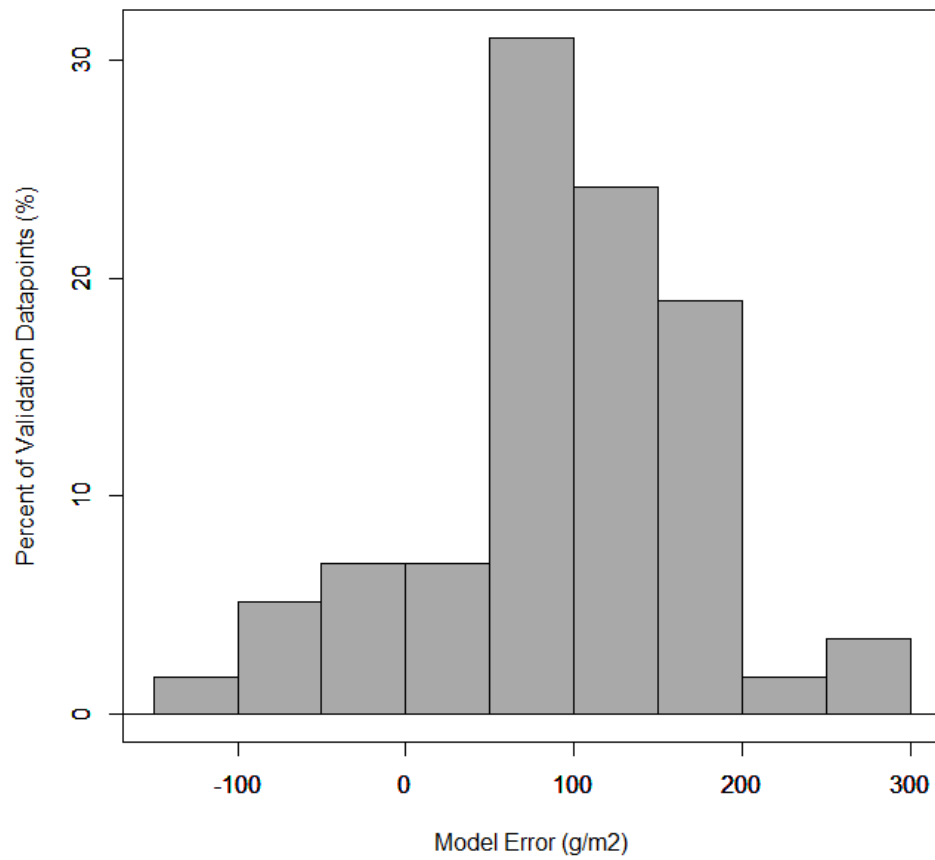


Table 6. Correlation coefficients matrix for predicted above-ground biomass, measured above-ground biomass, and biomass calibrated Landsat image.

	AGB_Predicted	AGB_Measured	AGB_Calibrated_RS
AGB_Predicted	1	0.34	0.41
AGB_Measured	0.34	1	0.61
AGB_Calibrated_RS	0.41	0.61	1

Section 3.2.1 identified areas in which the model could be improved to more accurately reflect biomass responses to training and land management practices. Additional sources of error in this validation are the actual inputs used to determine historical land management and training practices (Figure 22). Quantifying training loads has historically been a difficult issue for training land management (Koch et al. 2012). RFMSS was used to develop historical training loads. However, RFMSS is often used only as a planning database and does not always accurately depict training loads on the landscape. Additionally, the only haying data available were drawn from the 5-year agricultural outlease map with a training area resolution.

Figure 22. Histogram of model-predicted above-ground biomass error compared to measured above-ground biomass RTLA data.



## 4 Conclusions and Recommendations

### 4.1 Conclusions

This work developed the Optimal Allocation of Land for Training and Non-Training Uses (OPAL) Program to model and estimate the influences on military land use (training and non-training) on the dynamic and complex nature of above- and below-ground biomass. Specifically, this tool provides military land managers and the training community with the capability to estimate above- and below-ground biomass condition given different military training and land management impacts.

This phase of the project validated the OPAL tool by modeling and predicting below-ground biomass responses to training and land management practices at Fort Riley, KS. Data from a 4-year field study at Fort Riley, KS were used to estimate the model accuracy in predicting above- and below-ground biomass response to training and land management practices. The validation effort determined that the model-predicted values were fairly accurate for mowing and control conditions, but approximate 250 g/m<sup>2</sup> lower than measured values for burning conditions. This work concluded that the model generally underestimated the above-ground biomass compared with the plot data. Summarized across all samples, the mean above-ground biomass predicted by the model was 295 g/m<sup>2</sup> compared with a mean value of 375 g/m<sup>2</sup> for the observed plot data. The model was observed to be less sensitive to land management treatments in the short-term (weeks to months), but more sensitive to land management treatments in longer time-scales (months to years). When tested against training impacts, it was apparent that the model underestimated the impact of training on above-ground biomass compared with the field plot data.

In both above- and below-ground biomass estimations compared with the field plot data, the model did not predict instances where very large biomass values were observed in the field. The model correctly estimated only slight observed differences in below-ground biomass due to land management treatments over the short validation duration. However, the below-ground biomass estimates were approximately 300 g/m<sup>2</sup> lower than the measured data. The below-ground biomass model adequately predicted the trends between vehicle training treatments; however, it was not sensi-

tive enough to conditions that resulted in a wide range in values observed in the measured data.

A second validation was performed based on historic Fort Riley RTLA biomass data. While the field plot validation tested the accuracy of the model in predicting biomass responses to training and land management practices, it did not test the ability of the model to predict biomass across a large spatial area. While the model predicted smaller than observed values compared with the OPAL field data, it predicted values slightly larger than the Fort Riley RTLA data. On average, the model-predicted estimates 93.5 g/m<sup>2</sup> higher than the observed data.

Since the observations were composite samples, there were fewer extreme above-ground biomass measurements in the observations reducing the overall error of the model. The correlation coefficient of the predicted above-ground biomass and measured RTLA data was 0.34. The Fort Riley RTLA program had created an above-ground biomass map for the same sampling dates with a regression model of the RTLA vegetation data on NDVI measurements from Landsat imagery. The points extracted from the above-ground biomass map created by this method and the RTLA vegetation data points only had a correlation coefficient 0.07 higher (0.41) than the OPAL model output. This indicates that, even with a high resolution remote sensed image, the variability of the above-ground biomass is difficult to quantify.

The OPAL modeling tool successfully models and estimates the relative effects of different management scenarios on above- and below-ground biomass. For this purpose, absolute accuracy is not as critical as long as the model accurately predicts relative responses given management scenarios. With a minimal amount of inputs, the OPAL tool gives installation land managers the ability to estimate the response of the system to multiple management scenarios, and provides them with a common interface for discussions with range managers to minimize the maintenance requirements associated with training events.

## 4.2 Recommendations

To overcome the difficulty of predicting complex parameters and the errors observed in the validation efforts, it is recommended that the model be improved to more accurately reflect biomass responses to military and non-military practices by:

- Improving the accuracy of installation land management models and reducing the assumptions required to create those models by implementing higher level training and more rigorous land management schedules. This will reduce the large uncertainties and assumptions currently made in the schedules used to model the vegetation condition.
- Collect required data that monitor above- and below-ground biomass on a weekly or monthly interval (as opposed to annual sampling). This will help to overcome the lack of dynamic vegetation growth and death data, and will simplify the many assumptions currently required to create a weekly vegetation condition models.

It is further recommended that the OPAL tool be further developed to incorporate a remote sensing imagery capability and additional vegetation and soil condition indices (e.g., bulk density, vegetation quality, specific vegetation species monitoring, etc.).

It is also recommended that the OPAL modeling tool be adapted to estimate the cost of different scenarios to reach a desired vegetation condition.

## Acronyms and Abbreviations

Term	Definition
ACIS	Applied Climate Information System
AGB	Above-Ground Biomass
ATTACC	Army Training and Testing Area Carrying Capacity
CEERD	US Army Corps of Engineers, Engineer Research and Development Center
CERL	Construction Engineering Research Laboratory
DEM	Digital Elevation Model
DMPRC	Digital Multi-Purpose Range Complex
ERDC	Engineer Research and Development Center
ESA	US Endangered Species Act
FY	Fiscal Year
GIS	Geographic Information System
GPS	Global Positioning System
ID	Identification
INRMP	Integrated Natural Resources Management Plans
ISTVS	International Society for Terrain-Vehicle Systems
ITAM	Integrated Training Area Management
LCF	Land Condition Factor
LCTA	Land Condition-Trend Analysis
LIDAR	Light Detection and Ranging
LT	Light Tracking
MCF	MIM Conversion Factor
MIM	Maneuver Impact Mile
NA	Not Applicable
NDVI	Normalized Difference Vegetation Index
NRCS	Natural Resources Conservation Service
NREL	National Renewable Energy Laboratory
OPAL	Optimal Programming of Army Lands
PET	Potential Evapotranspiration
RCI	Rating Cone Index
RFMSS	Range Facility Management Support System
RTLA	Range and Training Land Assessment
RUSLE	Revised Universal Soil Loss Equation
SCL	Sandy Clay Loam
SICL	Silty Clay Loam
SRP	Sustainable Range Program
SSURGO	(USDA-NRCS) Soil Survey Geographical Database
T&E	Threatened and Endangered



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<b>Term</b>	<b>Definition</b>
TEPC	Threatened, Endangered, Proposed, and Candidate
TR	Technical Report
URL	Universal Resource Locator
USCS	Unified Soils Classification System
USDA	US Department of Agriculture
USDA-NRCS	US Department of Agriculture-Natural Resources Conservation Service
USHCN	US Historical Climatology Network
VCF	Vehicle Conversion Factor
VDMTS	Vehicle Dynamics Monitoring and Tracking System
VSF	Vehicle Severity Factor

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## Appendix A: Estimation of Mean Weekly PET

Evapotranspiration calculations are made based on the Blaney-Criddle Method. The Blaney-Criddle Method is a simple, empirical evapotranspiration model and is a function of average temperature and mean daily percentage of annual daytime hours (Brouwer Heibloem 1986, Schwab et al. 1993, see Table A-1):

$$ET_O = p * (0.46 * t_{mean} + 8) \quad (A1)$$

where:

$ET_O$  = Potential Evapo-transpiration rate (mm/day)

$P$  = mean daily percentage of annual daytime hours

$t_{mean}$  = mean weekly temperature (°C)

For the initial efforts a simplistic evapotranspiration model was used. For more accuracy, more complex models that take into account energy balances or solar radiation could be substituted.

Table A-1. The mean daily percentage of Annual Daytime Hours (p) for different latitudes.

	North	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec
Latitude	South	July	Aug	Sept	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	June
60°		0.15	0.20	0.26	0.32	0.38	0.41	0.40	0.34	0.28	0.22	0.17	0.13
55°		0.17	0.21	0.26	0.32	0.36	0.39	0.38	0.33	0.28	0.23	0.18	0.16
50°		0.19	0.23	0.27	0.31	0.34	0.36	0.35	0.32	0.28	0.24	0.20	0.18
45°		0.20	0.23	0.27	0.30	0.34	0.35	0.34	0.32	0.28	0.24	0.21	0.20
40°		0.22	0.24	0.27	0.30	0.32	0.34	0.33	0.31	0.28	0.25	0.22	0.21
35°		0.23	0.25	0.27	0.29	0.31	0.32	0.32	0.30	0.28	0.25	0.23	0.22
30°		0.24	0.25	0.27	0.29	0.31	0.32	0.31	0.30	0.28	0.26	0.24	0.23
25°		0.24	0.26	0.27	0.29	0.30	0.31	0.31	0.29	0.28	0.26	0.25	0.24
20°		0.25	0.26	0.27	0.28	0.29	0.30	0.30	0.29	0.28	0.26	0.25	0.25
15°		0.26	0.26	0.27	0.28	0.29	0.29	0.29	0.28	0.28	0.27	0.26	0.25
10°		0.26	0.27	0.27	0.28	0.28	0.29	0.29	0.28	0.28	0.27	0.26	0.26
5°		0.27	0.27	0.27	0.28	0.28	0.28	0.28	0.28	0.28	0.27	0.27	0.27
0		0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27

For implementation into the NetLogo model for Fort Riley, the values for 35° Latitude were plotted against the week of the year (Figure A-1).

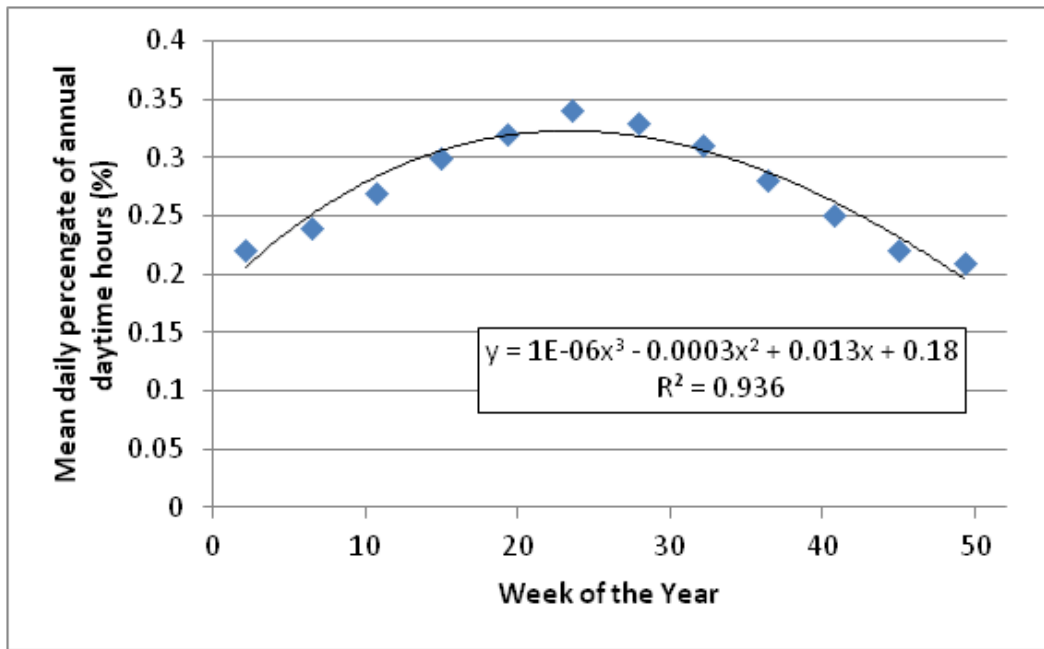


Figure A-1. Regression of mean daily percentage of annual daytime hours by week of the year for PET estimation.

A polynomial line was created from this data to develop a function estimating mean daily percentage of annual daytime hours using the week of the year:

$$p = 10^{-6} * w_{yr}^3 - 0.0003 * w_{yr}^2 + 0.013 * w_{yr} + 0.18 \quad (A1)$$

Using this regression, estimated weekly evapotranspiration per week can be calculated as:

$$ET_{week} = (10^{-6} * w_{yr}^3 - 0.0003 * w_{yr}^2 + 0.013 * w_{yr} + 0.18) * (0.46 * t_{mean} + 8) * 7/10 \quad (A2)$$

where:

- $ET_{week}$  = Potential weekly evapotranspiration rate in cm
- $w_{yr}$  = week of year from 1–52 (can get this number from the cumulative # of steps)
- $T_{mean}$  = Mean weekly temperature (°C) =  $(T_{max} + T_{min})/2$

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